

A mobility-aware 6G-enabled V2X communications using multi-user MC-CDMA-OTFS and car-following Markov mobility model with multi-agent deep Q-learning

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Abstract. This paper presents a novel 6G-Enabled vehicle-to-everything (V2X) communication framework designed for the Intelligent Internet of Vehicles (IoV). The proposed system integrates the multi-user access and interference suppression capabilities of multi-carrier code division multiple access (MC-CDMA) with the delay–Doppler domain robustness of orthogonal time frequency space (OTFS) modulation. This hybrid design ensures reliable transmission in high-mobility and dense vehicular environments. Vehicle mobility is modeled using a combination of car-following dynamics and Markov chain-based lane-changing behavior, capturing both longitudinal and lateral motion patterns. The communication system further employs minimum mean square error (MMSE) and zero-forcing (ZF) techniques for multi-user detection at the receiver. To cope with rapid channel variations caused by mobility, we introduce a Multi-Agent Deep Q-learning (DQL) framework for mobility-aware channel tracking. Each agent learns adaptive channel update strategies based on historical channel estimates and mobility context. Simulation results show that the proposed MC-CDMA–OTFS system with DQL tracking achieves up to a 2.5 dB SNR gain at $\text{BER} = 10^{-3}$ and improves throughput compared to a conventional OTFS baseline. These findings highlight the potential of the proposed hybrid design as a robust physical-layer foundation for next-generation 6G V2X networks.

Keywords: 6G, IoV, V2X, MC-CDMA, OTFS, multi-user, Markov chain.

Classification numbers: 4.2.3, 4.3.1.

1. INTRODUCTION

The rapid development of intelligent transportation systems (ITS) and the advent of fully autonomous vehicles have intensified the demand for ultra-reliable low-latency communication (URLLC), massive connectivity, and high-throughput data exchange. Although fifth generation (5G) networks support many vehicular services, they remain insufficient to meet the stringent requirements of sixth generation (6G)-enabled V2X systems, especially under extreme mobility, dense traffic, and highly dynamic scenarios [1, 2].

In the 6G-enabled V2X context, communication must evolve beyond conventional vehicle-to-vehicle (V2V) or vehicle-to-infrastructure (V2I) paradigms to enable semantic-level data fusion, cooperative perception, and intelligent coordination among thousands of mobile agents [3]. This necessitates waveforms that inherently resist high Doppler spreads and multipath fading. Orthogonal time-frequency space-time (OTFS) is a modulation method that operates in the Doppler-delay domain. OTFS has been shown to significantly outperform OFDM under extreme mobility conditions (up to 200 km/h) by maintaining robust BER even in dual-selective channels [4].

A key physical-layer challenge for OTFS is grid misalignment, where actual channel delays and Doppler shifts are fractional with respect to the system-defined bins. This mismatch causes energy leakage into neighboring delay-Doppler bins. It also introduces inter-symbol interference, which in turn degrades system performance. While maximum likelihood detection can accurately handle fractional shifts, its exhaustive search is computationally prohibitive for real-time V2X deployments [5].

Therefore, a 6G-enabled V2X communication system must be designed to meet several stringent performance requirements. First, it must effectively handle high Doppler shifts that occur in rapidly changing vehicular environments, where relative velocities between transmitters and receivers can reach hundreds of kilometers per hour [6]. Second, the system should support simultaneous access for many users, ensuring scalability in densely populated road networks and urban settings [7]. Third, it must guarantee reliable and stable connectivity over both line-of-sight (LOS) and non-line-of-sight (NLOS) links, particularly in complex topologies such as tunnels, intersections, and urban canyons [8, 9]. Finally, the system should leverage delay-Doppler domain diversity to enhance signal robustness and maintain communication performance under severe multipath and mobility-induced fading conditions [10].

Despite these advances, there remains a gap for a unified V2X framework that supports large-scale user connectivity and ensures performance across LOS and NLOS conditions while exploiting delay-Doppler diversity for resilience. This motivates our proposed integration of MC-CDMA, OTFS, and multi-agent deep Q-learning for adaptive, scalable, and robust 6G-enabled V2X communications.

1.1. Related works

MC-CDMA is a well-established multi-user access technique that overlays code division multiple access spreading on top of orthogonal frequency division multiplexing. By assigning each user a unique spreading sequence, such as Gold or Walsh-Hadamard codes, MC-CDMA enables simultaneous transmission over frequency-selective fading channels while maintaining spectral efficiency [11]. Its inherent advantages include frequency diversity, robustness to narrowband interference, and relatively simple implementation.

In the domain of vehicular communications, MC-CDMA has been investigated for its ability to support multiple high-speed users sharing the same spectrum [12]. However, its effectiveness diminishes in high-mobility scenarios where the assumption of quasi-static frequency channels no longer holds. Rapid Doppler variations cause inter-carrier interference (ICI) and destroy code orthogonality, leading to increased multi-user interference. Additionally, MC-CDMA requires strict timing and frequency synchronization among users. This condition is difficult to guarantee in practical, dynamic V2X environments [13].

To overcome these limitations, OTFS has emerged as a robust alternative modulation scheme tailored for doubly dispersive channels. OTFS transforms symbols into the delay-

Doppler domain, where the wireless channel exhibits sparsity and relative time-invariance, allowing more reliable performance under severe Doppler and multipath conditions [14], a Wavelet-aided OTFS method using 2-D multicarrier modulation format for high mobility communications is introduced in [15]. Various channel estimation strategies have been developed for GFDM, and OTFS in impulsive noise channels have been evaluated in [16].

Li *et al.* [17] studied mmWave user multi-association in a two-tier heterogeneous ultra-dense network (HetUDN) with a relatively large number of user equipments (UEs). A framework of multi-agent reinforcement learning (MARL) is proposed to tackle the complicated optimization problem, leveraging its adaptivity to the communication environment. The proposed scheme considers mmWave beam-division based multi-connectivity and takes advantage of a macro base station (MBS) for indirect cooperation among agents (UEs). In [18], the OTFS known as a popular 6G candidate solution with enhanced spectral efficiency in high-mobility environments, is combined with NOMA over Rayleigh fading channels. In addition, a DL-based signal detection approach for the OTFS-NOMA scheme is proposed, where the network is trained to distinguish and decode the signals effectively.

Recent studies have focused on resource optimization in next-generation V2X communications. The work in [19] provided a comprehensive survey of mathematical models for resource allocation in V2X sidelinks, especially towards 6G URLLC systems. The authors classify the techniques into centralized, distributed, and reinforcement learning optimization, and point out the main challenges such as nonlinearity of the network environment, and propose solutions based on game theory and deep learning. Meanwhile, Jamal *et al.* [20] proposed a multi-agent reinforcement learning (MARL) model to optimize spectrum sharing among vehicles in dynamic V2X environments. The system uses a combination of DQN and cooperative policies, showing the ability to adapt to rapidly changing environments and improving reliability and spectrum efficiency compared to traditional methods.

Despite these developments, existing literature tends to address MC-CDMA, OTFS, or multi-agent reinforcement learning independently. To the best of our knowledge, no prior work has unified MC-CDMA for multi-user access, OTFS for delay-Doppler robustness, and multi-agent deep Q-learning for channel tracking under a comprehensive framework tailored for 6G-enabled V2X systems. This paper addresses that gap by proposing a hybrid architecture that combines code-domain spreading, delay-Doppler diversity, and intelligent, mobility-aware learning agents based on realistic vehicle dynamics, including car-following and Markov-based Lane transitions. The resulting system is scalable, adaptive, and well-suited to the highly dynamic conditions of next-generation vehicular networks.

Moreover, the novelty of our work lies not only in this unique integration, but also in the comprehensive evaluation under realistic conditions, incorporating an IDM-based longitudinal model, Markov chain lane-change behavior, stochastic Rician fading channels, and varying multi-user interference levels. Such a combined evaluation framework, bridging physical-layer design and mobility-aware adaptation, has not been presented in the existing 6G V2X literature.

1.2. Motivation and our contributions

In this paper, we focus on the design of a 6G-Enabled V2X communication framework that emphasizes high-speed, collaborative, and reliable connectivity for the Intelligent Internet of Vehicles (IoV). Our idea is to combine the high spectral efficiency and robustness of multicarrier modulation schemes, such as Orthogonal Time Frequency Space (OTFS), with the

interference suppression and user separation capabilities of Code Division Multiple Access (CDMA). OTFS has recently emerged as a promising modulation technique for high-mobility scenarios due to its ability to represent time-varying channels in the delay–Doppler domain, enabling enhanced diversity and near-constant channel conditions per symbol. When integrated with multi-user MC-CDMA spreading, the resulting hybrid system inherits the resilience of OTFS against Doppler effects, while benefiting from the multi-access and security features of the CDMA paradigm.

To address the challenges of high mobility and ensure signal robustness in dynamic V2X environments, we propose a novel hybrid communication framework that combines the strengths of MC-CDMA and OTFS, and a Multi-Agent Deep Q-Learning algorithm for Mobility-Aware Channel Tracking to learn optimal channel update strategies. By integrating multi-user spreading with delay–Doppler domain processing, the system aims to support reliable and scalable 6G vehicular communications.

Our approach to design of a 6G-Enabled V2X communication is as follows:

- 1) Designing a joint MC-CDMA–OTFS transmission scheme that leverages code-domain user separation and delay–Doppler resilience.
- 2) Modeling realistic vehicle mobility using Car-Following dynamics and Markov-based lane-change behavior.
- 3) Mobility-aware channel tracking. For each user, a DQL agent observes recent channel estimates, mobility indicators (velocity, acceleration), and Markov-based transition probabilities to select optimal update strategies (e.g., Doppler compensation, Kalman-type filtering).
- 4) Comparative evaluation of the proposed system against standalone MC-CDMA and OTFS in terms of BER performance under various Doppler and user density conditions.

This combined MC-CDMA–OTFS approach offers a flexible and powerful solution for V2X environments characterized by rapid mobility, dense traffic, and dynamic topologies. It enables high-capacity access, robust signal detection under fast fading, and support for secure and reliable vehicle communication, all essential features in the 6G vision for autonomous transportation systems.

Our contributions in this paper are summarized as follows:

- 1) Hybrid MC-CDMA–OTFS Framework for 6G V2X that combines MC-CDMA and OTFS to support multi-user access in high-mobility vehicular environments. The scheme exploits spreading codes for user separation and delay–Doppler processing for robustness against Doppler effects and time-varying channels.
- 2) Realistic Mobility and Channel Modeling: A hybrid mobility model is developed based on Car-Following dynamics and Markov Chain based lane changes, capturing realistic vehicle behavior in highway and urban scenarios. The wireless channel is modeled using Rician fading with varying Doppler and path loss conditions typical in V2X.
- 3) Mobility-Aware Channel Tracking via Multi-Agent Deep Q-Learning: A DQL-based tracking agent is integrated into the receiver to learn optimal channel update strategies from historical CSI and mobility context, including velocity, acceleration, and transition probabilities. This enables adaptive and low-error tracking of delay–Doppler channels in dynamic scenarios

4) Comprehensive BER Performance Evaluation: We implement extensive simulations to compare the proposed system against standalone MC-CDMA and OTFS baselines. The results demonstrate significant gains in BER performance under high user density and severe Doppler shifts, validating the effectiveness of the combined approach.

The remainder of this paper is organized as follows. Section 2 presents the proposed system model. Section 3 reports the simulation results and evaluates the performance of the proposed framework. Section 4 concludes the paper with final remarks and suggestions for future research.

Throughout the paper, bold uppercase letters denote matrices, bold lowercase letters denote vectors, $(\cdot)^T$ and $(\cdot)^H$ represent the transpose and Hermitian transpose, respectively.

2. PROPOSED SYSTEM MODEL

2.1. Signal model

Consider a combined MC-CDMA-OTFS transmission system that simultaneously serves U user equipments (UEs), as illustrated in Figure 1. Each user $u \in \{1, 2, \dots, U\}$ generates a binary input bitstream $\mathbf{d}_u = \{d^{(u)}[i]\}$, where $d^{(u)}[i] \in \{-1, +1\}$ with equal probability, and T_b denotes the bit duration.

The binary data stream is first passed through a channel encoder and scrambler to ensure symbol independence under noise and to improve robustness. The encoded bits are then mapped into complex symbols using standard modulation schemes (e.g., BPSK, QPSK, QAM), yielding a modulated symbol sequence $\mathbf{x}_u = \{x_u(n)\}$, $n = 0, \dots, N_s - 1$. This data symbol is then copied into N_c subcarriers, and multiply by the spreading code $\mathbf{c}_u = \{c_u(k)\}$, $k = 0, 1, \dots, N_c - 1$ of user u . The MC-CDMA spread signals from all users are superimposed in the time-frequency (TF) domain as follows:

$$\mathbf{S}[n, k] = \sum_{u=1}^U \mathbf{s}^{(u)}[n, k] = \sum_{u=1}^U x_u(n) c_u(k) \in \mathbb{C}^{N_s \times N_c} \quad (1)$$

This results in a composite MC-CDMA symbol vector of size N_c , to be mapped into the OTFS frame.

OTFS pre-processing and Heisenberg Transform: To combat channel variations due to vehicular mobility, the MC-CDMA composite signal $\mathbf{S}[n, k]$ is reshaped into a two-dimensional grid $\mathbf{X}_{\text{DD}}[k, l] \in \mathbb{C}^{N \times M}$, representing data in the delay-Doppler (DD) domain, where $N = N_s$ is number of Doppler bins (time slots), $M = N_c$ is number of delay bins (subcarriers), $k \in \{0, \dots, N-1\}$, $l \in \{0, \dots, M-1\}$. The DD domain signal is converted into the TF domain via the Inverse Symplectic Finite Fourier Transform (ISFFT):

$$\mathbf{X}_{\text{TF}}[n, m] = \frac{1}{\sqrt{MN}} \sum_{k=0}^{N-1} \sum_{l=0}^{M-1} \mathbf{X}_{\text{DD}}[k, l] \cdot e^{j2\pi \left(\frac{nk}{N} - \frac{ml}{M} \right)} \quad (2)$$

The TF domain signal is converted to a time-domain waveform via the Heisenberg transform, using a transmit pulse $g_{\text{tx}}(t)$:

$$s(t) = \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} \mathbf{X}_{\text{TF}}[n, m] \cdot g_{\text{tx}}(t - nT) \cdot e^{j2\pi m \Delta f (t - nT)} \quad (3)$$

Equation (3) applies the Heisenberg transform to convert the time–frequency (TF) domain signal into a continuous-time waveform $s(t)$ suitable for transmission. In this expression, $g_{tx}(t)$ is the transmit pulse shaping filter, $\mathbf{X}_{TF}[n, m]$ denotes the TF symbol at time index n and subcarrier index m , and T and Δf represent the symbol duration and subcarrier spacing, respectively.

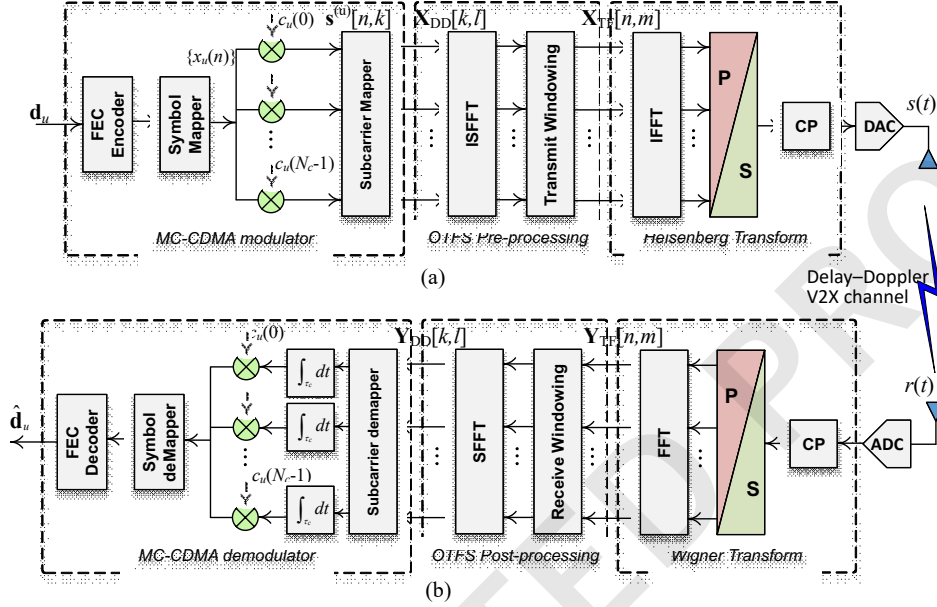


Figure 1. Proposed multi-user MC-CDMA–OTFS system: (a): transmitter; (b): receiver.

The double summation reflects the modulation process across both time and frequency dimensions, where each TF symbol is modulated by a frequency-shifted and time-shifted version of the transmit pulse. This step ensures that the composite MC-CDMA–OTFS signal is correctly shaped for propagation through the doubly dispersive V2X channel.

This signal is then transmitted through a doubly dispersive V2X channel characterized by delay–Doppler response $h(\tau, \nu) = \sum_{i=1}^P h_i \delta(\tau - \tau_i) \delta(\nu - \nu_i)$ as:

$$r(t) = \iint h(\tau, \nu) \cdot s(t - \tau) \cdot e^{j2\pi\nu(t - \tau)} d\tau d\nu \quad (4)$$

Wigner Transform and OTFS post-processing: At the receiver, we have the received signal $r(t)$. This signal is then filtered using $g_{rx}(t)$ and transformed via the Wigner transform to recover the TF samples:

$$\mathbf{Y}_{TF}[n, m] = \int g_{rx}^*(t - nT) \cdot r(t) \cdot e^{-j2\pi m \Delta f (t - nT)} dt \quad (5)$$

The Wigner transform in Equation (5) is used at the receiver to map the received time-domain signal $r(t)$ back into the time–frequency (TF) domain after matched filtering with the receive pulse $g_{rx}(t)$. In the context of OTFS post-processing, this operation extracts the TF samples $\mathbf{Y}_{TF}[n, m]$ corresponding to each time slot n and subcarrier k .

The receive pulse $g_{rx}(t)$ is typically designed to be bi-orthogonal (or matched) to the transmit pulse $g_{tx}(t)$ to minimize inter-symbol interference (ISI) and inter-carrier interference

(ICI). The integration in the Wigner transform captures both time localization (via $t-nT$) and frequency localization (via $e^{-j2\pi m\Delta f(t-nT)}$), enabling precise recovery of the TF-domain representation before converting it back to the delay-Doppler domain using the symplectic finite Fourier transform (SFFT).

This step effectively reverses the Heisenberg transform at the transmitter, allowing the OTFS demodulator to reconstruct the delay-Doppler symbols while preserving the channel's Doppler and delay characteristics.

The TF signal is mapped back to the delay-Doppler domain via SFFT:

$$\mathbf{Y}_{\text{DD}}[k, l] = \frac{1}{\sqrt{MN}} \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} \mathbf{Y}_{\text{TF}}[n, m] \cdot e^{j2\pi \left(\frac{ml}{M} - \frac{nk}{N} \right)} \quad (6)$$

The input-output relationship of the OTFS system in the DD domain can be expressed as a 2D discrete convolution:

$$\mathbf{Y}_{\text{DD}}[k, l] = \sum_{k'=0}^{N-1} \sum_{l'=0}^{M-1} \mathbf{X}_{\text{DD}}[k', l'] \cdot h_w[k-k', l-l'] + v[k, l] \quad (7)$$

where $\mathbf{X}_{\text{DD}}[k', l']$ is the transmitted symbol, $\mathbf{Y}_{\text{DD}}[k, l]$ is the received symbol, $h_w[\cdot, \cdot]$ is the equivalent channel response in the DD domain, accounting for delay and Doppler shifts, $v[k, l]$ is the additive noise. This model captures the effects of the doubly dispersive wireless channel in the DD domain, where each received symbol is affected by multiple transmitted symbols due to channel spread in both delay and Doppler.

2.2. Mobility model

The vehicle mobility is modeled by combining the Intelligent Driver Model (IDM) for longitudinal behavior with a Markov Chain-based lane-changing model for lateral movement as shown in Figure 2. The acceleration of i -th vehicle is determined by:

$$\dot{v}_i(t) = a \left[1 - \left(\frac{v_i(t)}{v_0} \right)^\delta - \left(\frac{s^*(v_i, \Delta v_i)}{s_i(t)} \right)^2 \right] \quad (8)$$

where $v_i(t)$ is velocity of vehicle, v_0 is desired velocity, δ is acceleration exponent (typically $\delta=4$), a is maximum acceleration, $s_i(t)$ is actual gap between i -th vehicle and the vehicle in front, $\Delta v_i(t) = v_i(t) - v_{i-1}(t)$ is relative velocity with respect to the vehicle ahead, respectively.

The desired gap (safe distance) function is defined as:

$$s^*(v_i, \Delta v_i) = s_0 + v_i T + \frac{v_i \Delta v_i}{2\sqrt{ab}} \quad (9)$$

where s_0 is minimum safety distance, T is safe time headway, and b is comfortable deceleration.

Next, we define the Lane-Change model using Markov Chains as follows. Assuming the lane change occurs in time τ_{LC} , with the distance between the two lanes being d_{Lane} , then the average lateral velocity is:

$$v_{\perp}(t) = \frac{d_{\text{Lane}}}{\tau_{LC}} \quad (10)$$

Based on the Markov lane-change model, we have P_{LC} as the lane change probability. From this, the expected lateral velocity is:

$$E\{v_{\perp}(t)\} = P_{LC} \cdot \frac{d_{Lane}}{\tau_{LC}} \quad (11)$$

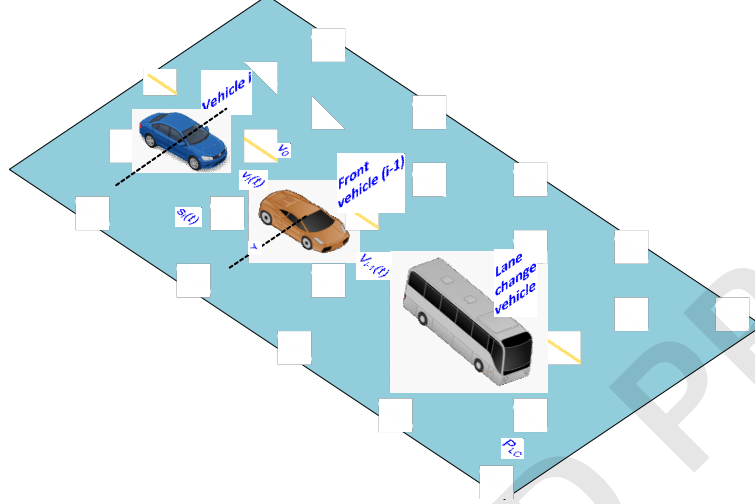


Figure 2. IDM for longitudinal dynamics and Markov chain lane change model.

The effective relative velocity between BS and vehicle is:

$$v_{\text{ref}}(t) = \|\vec{v}_{\text{relative}}(t)\| = \sqrt{v_{\parallel}^2(t) + v_{\perp}^2(t)} \quad (12)$$

Consider i -th vehicle we have $v_{\parallel}(t) = v_i(t)$.

2.3. Channel model

To model the propagation loss in V2X communication, we start with the free-space path loss (FSPL) $PL_{fs}(d) = (4\pi df/c)^2$, typically expressed in dB as:

$$PL_{fs}(d) = 20\log_{10}(d) + 20\log_{10}(f) + 20\log_{10}\left(\frac{4\pi}{c}\right) \quad (13)$$

where d is the distance between the base station (BS) and the user equipment (UE), f is the carrier frequency in Hz, and c is the speed of light. In practical V2X environments, transmitted signals propagate through multiple paths, resulting in attenuation, delay, phase shift, and angular dispersion at the receiver. According to the Friis transmission equation for mmWave communications, the received power is linearly proportional to the transmit power P_t , antenna gains G_t , G_r , and the square of the carrier wavelength, while inversely proportional to the path distance and an environment-dependent attenuation factor γ :

$$P_r = P_t \left(\frac{\lambda}{4\pi d} \right)^2 G_t G_r e^{-\gamma d} \quad (14)$$

Furthermore, when the transmitter and receiver are elevated above ground, the received power also becomes linearly dependent on the antenna heights h_t and h_r , due to additional ground reflection and diffraction effects. The received power is:

$$P_r = P_t \left(\frac{h_t h_r}{d^2} \right) G_t G_r \quad (15)$$

Rician fading model: In scenarios where a dominant line-of-sight (LOS) path exists between the transmitter and receiver, the small-scale fading can be modeled using the Rician distribution. Rician Fading Channel Model with Doppler shift is represented as:

$$H(t) = \sqrt{\frac{K(t)}{K(t)+1}} \cdot h_{LOS}(t) + \sqrt{\frac{1}{K(t)+1}} \cdot h_{NLOS}(t) \quad (16)$$

where $h_{LOS}(t) = e^{j2\pi f_D(t)t}$ is Doppler phase of LOS component, $h_{NLOS}(t) \sim \text{CN}(0,1)$ is random fading, $K(t)$ is Rician coefficient, characterizing the LOS/NLOS ratio at time t . The Doppler shift based on relative velocity between vehicles is calculated as:

$$f_D(t) = \frac{v_{ref}(t)}{\lambda} = \frac{1}{\lambda} \cdot \frac{d}{dt} d_{u2s}(t) \quad (17)$$

where $\lambda = c/f$ is wavelength, $v_{ref}(t)$ is relative velocity between BS and vehicle which is calculated by (12).

K-factor model which depends on satellite distance is expressed as:

$$K(t) = K_0 \cdot \left(\frac{d_0}{d_{u2s}(t)} \right)^\gamma \quad (18)$$

where K_0 is LOS coefficient at standard distance d_0 , γ is attenuation factor. When $K=0$, the LOS component disappears, and the channel reduces to a Rayleigh fading model.

2.4. Multi-user detection

After OTFS demodulation and inverse spreading in the receiver, the combined received signal across all users in the delay–Doppler domain can be expressed as:

$$\mathbf{Y}_{DD} = \mathbf{H} \cdot \mathbf{X}_{DD} + \mathbf{v} \quad (19)$$

where $\mathbf{Y}_{DD} \in \mathbb{C}^{N_c \times 1}$ is received signal vector (after OTFS demodulation), $\mathbf{X}_{DD} \in \mathbb{C}^{U \times 1}$ is transmitted symbols from U users, $\mathbf{H} \in \mathbb{C}^{N_c \times U}$ is effective multi-user channel matrix after spreading and delay–Doppler propagation, and $\mathbf{v}$ is additive white Gaussian noise, which is modelled as $\mathbf{v} \sim \text{CN}(\mathbf{0}, \sigma^2 \mathbf{I})$. Intuitively, each element of $\mathbf{Y}_{DD}$ results from the superposition of shifted versions of all users' DD symbols, weighted by their respective DD channel responses.

To estimate the transmitted symbols $\mathbf{X}_{DD}$, we consider two linear detection techniques: Zero Forcing (ZF) and Minimum Mean Square Error (MMSE) Detection.

ZF detection: this is a simple and effective technique for eliminating inter-user interference by applying the pseudo-inverse of the channel matrix to the received signal. ZF ensures complete removal of interference in the absence of noise, but it amplifies noise, especially when $\mathbf{H}$ is ill-conditioned or has closely correlated columns [21]. Once the received vector $\mathbf{Y}_{DD}$ is modeled by Eq. (19), a straightforward linear detection strategy is to nullify multi-user interference (MAI) by applying the pseudo-inverse of the effective channel matrix $\mathbf{H}$. The ZF detector completely removes cross-user interference under perfect channel knowledge, but

does not account for noise, which may be amplified if $\mathbf{H}$ is ill-conditioned. The ZF filter for u -th UE is:

$$\mathbf{w}_u^{\text{ZF}}(t) = \left[\left(\mathbf{H}^H(t) \mathbf{H}(t) \right)^{-1} \mathbf{H}^H(t) \right]_{:,u} \quad (20)$$

MMSE detection: MMSE detection improves upon ZF by considering both interference and noise. It minimizes the mean square error between the transmitted and estimated signals. The MMSE filter for u -th UE is:

$$\mathbf{w}_u^{\text{MMSE}}(t) = \left[\left(\mathbf{H}^H(t) \mathbf{H}(t) + \sigma^2 \mathbf{I} \right)^{-1} \mathbf{H}^H(t) \right]_{:,u} \quad (21)$$

where σ^2 is the noise variance, $\mathbf{I}$ is the identity matrix of size $U \times U$.

This formulation balances interference suppression with noise resilience, making MMSE more robust than ZF in ill-conditioned channels, high Doppler spreads, or dense multi-user interference scenarios. MMSE provides better robustness in noisy and fading conditions by balancing interference suppression and noise amplification. It is widely used in MIMO and multicarrier systems such as OFDM and MC-CDMA. MMSE performs more robustly than ZF in practical V2X environments [22] with channel fading and additive noise, especially under high Doppler spreads [23].

2.5. Mobility aware channel tracking using multi-agent deep Q-learning

2.5.1. Stochastic optimization problem formulation

In high-mobility V2X environments, rapid variations in velocity and channel conditions cause severe Doppler shifts and fast-fading effects, which degrade the reliability of communication. To maintain robust performance, it is essential to accurately track the time-varying delay-Doppler channel response $\mathbf{H}_u(t)$ and ensure the estimated channel $\hat{\mathbf{H}}_u(t)$ that leads to high-quality signal detection. In this context, the core objective of our proposed framework is to maximize the signal-to-interference-plus-noise ratio (SINR) at the receiver through intelligent, mobility-aware channel tracking.

The instantaneous SINR for user u at time t is given by:

$$\text{SINR}_u(t) = \frac{P_u \cdot \left| \mathbf{w}_u^H(t) \cdot \hat{\mathbf{H}}_u(t) \right|^2}{\sum_{j \neq u} P_j \cdot \left| \mathbf{w}_u^H(t) \cdot \hat{\mathbf{H}}_j(t) \right|^2 + \sigma^2} \quad (22)$$

where P_u is the transmit power of user u , $\mathbf{w}_u(t)$ is the ZF filter or MMSE filter, $\hat{\mathbf{H}}_u(t)$ is the estimated channel for user u , σ^2 is the noise power, $\hat{\mathbf{H}}_j(t)$ represents the estimated channel of interfering users.

We model the problem as a Markov Decision Process (MDP), where each user u is assigned an autonomous agent that selects an optimal channel tracking action a_t^u based on the observed state s_t^u at time t . The agent's goal is to learn a policy $\pi: \mathcal{S} \rightarrow \mathcal{A}$ that maximizes the expected long-term SINR improvement.

In this formulation, the state encapsulates the most recent channel estimates in the delay–Doppler domain, user mobility features (velocity, acceleration), and Markov-based lane-change indicators. The action space consists of candidate channel update strategies, such as Doppler compensation, delay bin adjustment, reinitialization, or adaptive filtering. The reward quantifies the accuracy of the updated channel estimate in terms of the resulting SINR, thereby linking physical-layer channel tracking quality to the agent’s decision-making. This structure allows each agent to adapt its channel tracking strategy dynamically according to real-time mobility and channel variations, enabling robust performance even in fast-changing V2X environments. The optimization problem is then defined as:

$$\begin{aligned} \pi^* &= \arg \max_{\pi} \mathbb{E}_{\pi} \left[\sum_{t=0}^T \gamma^t \cdot \text{SINR}_u(t) \right] \\ \text{s.t. } &\sum_{u=1}^U P_u \leq P_m \end{aligned} \quad (23)$$

where P_m denotes the maximal transmit power of the BS, subject to the per-user power and system constraints.

The Q-value of agent u is defined as follows:

$$Q^u(s_t^u, a_t^u; \theta^u) = \mathbb{E} \left[\sum_{k=0}^{\infty} \gamma^k \cdot \text{SINR}_u(t+k) | s_t^u, a_t^u \right] \quad (24)$$

where $\gamma \in (0,1)$ is a discount factor controlling the trade-off between immediate and future SINR gains. The Q-value represents the expected cumulative reward when agent u takes action a in state s and subsequently follows the current policy. In our context, this quantifies the long-term SINR improvement achievable by applying a given channel tracking strategy in the observed mobility and channel conditions.

2.5.2. State, action and reward design

- **State** $s_t^u \in \mathcal{S}$: In the proposed MDP formulation, the state of agent u at time t encapsulates: Channel observations: most recent delay–Doppler channel estimates $\hat{\mathbf{H}}_u(t-1), \hat{\mathbf{H}}_u(t)$, capturing both magnitude and phase response; Mobility indicators: estimated user velocity $v_u(t)$, acceleration $a_u(t)$ derived from the IDM-based longitudinal model; Lane-change dynamics: the Markov chain lane-switching probability $p_{\text{switch}}(t)$, representing lateral motion behavior; Historical CSI tracking quality: past estimation errors to help the agent infer temporal channel evolution trends.

The state space in the DQL framework is presented by:

$$s_t^u = \left[\hat{\mathbf{H}}_u(t-1), \hat{\mathbf{H}}_u(t), v_u(t), a_u(t), p_{\text{switch}}(t) \right] \quad (25)$$

- **Action** $a_t^u \in \mathcal{A}$: The agent selects channel tracking strategies, including: Linear extrapolation based on $\hat{\mathbf{H}}_u(t-1)$, Doppler shift compensation and delay bin adjustment, Reinitialization of channel estimate, and adaptive Kalman-type filtering update. Besides, full reinitialization of the channel estimates when severe mismatch is also detected.

- **Reward** $r_t^u \in \mathbb{R}$: The reward function ensures accurate tracking, and it is defined as:

$$r_t^u = -\frac{\|\hat{\mathbf{H}}_u(t) - \mathbf{H}_u(t)\|_F^2}{\|\mathbf{H}_u(t)\|_F^2} \quad (26)$$

where $\hat{\mathbf{H}}_u(t)$ is the predicted channel and $\mathbf{H}_u(t)$ is the actual which is measured value and $\|\cdot\|_F$ denotes the Frobenius norm.

The reward function measures the accuracy of the updated channel estimate in terms of its impact on SINR. A higher (less negative) reward indicates that the predicted channel closely matches the true channel, which leads to more accurate detection and higher SINR. Conversely, large estimation errors result in more negative rewards, penalizing strategies that degrade channel tracking quality.

This formulation ensures that the reward directly reflects physical-layer performance, while also being differentiable and suitable for optimization via deep Q-learning. Since the channel estimation error inherently captures the effects of both Doppler-induced variations and multi-user interference, the agent learns strategies that are robust across a wide range of high-mobility V2X scenarios.

- **Policy** $\pi(s_t^u)$: A deep neural network approximates the Q-function $Q^u(s_t^u, a_t^u; \theta^u)$. Once the Q-value function has been learned for each agent u , the policy $\pi(s_t^u)$ determines which channel tracking action should be selected for a given observed state s . The optimal policy aims to choose the action that maximizes the expected long-term cumulative reward, thereby ensuring sustained high SINR performance under dynamic mobility and channel conditions.

The optimal action is selected as:

$$a_t^{u*} = \arg \max_{a \in A} Q^u(s_t^u, a_t^u; \theta^u) \quad (27)$$

where A denotes the finite action set of possible channel tracking strategies.

In practical implementation, we adopt an ε -greedy strategy to balance exploration and exploitation:

- **Exploitation**: with probability $1 - \varepsilon$, select the action that maximizes the current Q-value estimate for the given state.
- **Exploration**: with probability ε , select a random action to explore potentially better strategies and avoid local optima.

This approach allows agents to continuously adapt to varying channel statistics and mobility patterns, learning to apply Doppler compensation, delay bin adjustment, or reinitialization at the most beneficial moments. Over time, the learned policy converges toward a stable mapping from mobility-channel states to optimal tracking actions, leading to consistently improved BER and SINR in high-mobility 6G V2X networks.

The learned policy enables real-time tracking of fast-varying OTFS channels under high Doppler and delay spread, significantly enhancing demodulation and MC-CDMA multi-user detection accuracy.

Proposed Algorithm for Mobility-Aware Channel Tracking via Multi-Agent Deep Q-Learning is as follows:

Algorithm 1. Mobility-aware channel tracking via multi-agent deep Q-learning.

```

1: Initialize Q-network parameters  $\theta_u$  randomly for each user  $u$ 
2: Initialize target network  $Q_u'$  with weights  $\theta_u' \leftarrow \theta_u$ 
3: Initialize replay buffer  $D_u \leftarrow \emptyset$  for each agent  $u$ 
4: for  $t = 1$  to  $T$  do
5:   for each user  $u = 1$  to  $U$  do
6:     Observe current state:  $s_t^u = \{\hat{\mathbf{H}}_u(t), v_u(t), a_u(t), p_{\text{switch}}^u(t)\}$ 
7:     if  $c \leq \varepsilon$  then
8:       Select random action  $a_t^u \in A$  with probability  $\varepsilon$ 
9:     else
10:      Select action  $a_t^u = \arg \max_{a \in A} Q_u(s_t^u, a; \theta_u)$ 
11:    end if
12:    Apply action  $a_t^u$  to update CSI estimate:
        
$$\hat{\mathbf{H}}_u(t) \leftarrow \text{Channel\_Update}(\hat{\mathbf{H}}_u(t-1), a_t^u)$$

13:    Compute reward according to (26) after applying  $\hat{\mathbf{H}}_u(t)$ 
14:    Observe next state  $s_{t+1}^u \leftarrow \{CSI\_obs_u(t+1), v_u(t+1), \dots\}$ 
15:    Store transition  $(s_t^u, a_t^u, r_t^u, s_{t+1}^u)$  in  $D_u$ 
16:  end for
17:  for each user  $u = 1$  to  $U$  do
18:    Sample mini batch of  $B$  transitions from  $D_u$ 
19:    for each sample  $(s, a, r, s')$ , calculate:
        
$$y_t^u = r_t^u + \gamma \cdot \max_{a' \in A} Q_u(s_{t+1}^u, a'; \theta_u')$$

20:    Perform gradient descent step on loss:
        
$$L_u = \left( Q_u(s_t^u, a_t^u; \theta_u) - y_t^u \right)^2$$

21:    Periodically update target network:  $\theta_u' \leftarrow \theta_u$ 
22:  end for
23: end for
24: return: Final learned policies  $\pi_u(s) = \arg \max_a Q_u(s, a; \theta_u)$ 

```

In proposed Algorithm 1, we employ a set of DQL agents, each assigned to a specific user, to learn adaptive channel tracking policies in dynamic V2X environments. At each step t , an agent observes its local state, including current CSI and mobility features such as velocity, acceleration, and lane-switching probability, and selects an optimal channel update action to maximize the resulting SINR. The Q-function is trained using temporal-difference learning with experience replay and a target network. This multi-agent framework enables decentralized, low-complexity, and mobility-aware tracking of delay-Doppler channels, ensuring reliable multi-user communication under high mobility and rapidly varying wireless conditions.

3. SIMULATION RESULTS

In this section, the numerical results are presented. The Monte-Carlo simulation is used to evaluate the system performance to verify the efficiency of the proposed system in different simulation conditions. The simulation is used to evaluate the performance of the proposed system and estimate the impact of parameters on the performance of the whole system.

3.1. Simulation setup

This section presents experimental setup, test scenarios, simulation parameters and configuration settings to implement the proposed system model and algorithm. The simulation parameters are listed in Table 1. For BER simulation, 5×10^6 channel realizations are implemented to evaluate the system performance. The simulation parameters are listed in Table 1.

Table 1. The simulation parameters.

Parameter	Value
Carrier frequency f_c	12 GHz
Bandwidth	10 MHz
Number of subcarriers M	64
Number of Doppler bins N	64
Modulation	BPSK / QPSK
Number of users U	{2, 4, 8}
User speed	100-175 Km/h
Lane-change probability	{0.05, 0.1, 0.2}
Spreading codes	Gold / Hadamard / Zadoff-Chu
OTFS grid size	$N \times M = 64 \times 64$
Channel	Rician fading, $K = \{0, 5, 10\}$ dB
Doppler shift	up to 500 Hz
Delay spread	3 taps
Noise model	AWGN

Table 2. Hyperparameters and reproducibility settings for DQL models.

Parameter	Value
Learning Hyperparameters	
Learning rate	0.001
Discount factor	0.99
Replay buffer size	50,000
Batch size	64
Target network update period (steps)	1,000
Epsilon decay schedule	1.0 0.05 over 50k steps
Gradient clipping (L_2 norm)	≤ 10
Reproducibility Settings	
Random seeds	12345
cuDNN deterministic mode	Enabled (benchmark OFF)
Weight initialization	Xavier uniform
Number of independent training runs	3

All simulations were conducted on a workstation equipped with an Intel E5-1603 v3 @ 2.80 GHz CPU, 15.8 GB RAM, and an NVIDIA GTX 1050 Ti (4 GB) GPU, running Python 3.12. The Rician fading channel model considers K -factors of 0 dB, 5 dB, and 10 dB to represent NLOS to strong LOS conditions, with Doppler shifts up to 500 Hz and 3-tap delay spread. Both Gold, Hadamard, and Zadoff-Chu spreading codes are examined for $U = \{2, 4, 8\}$

users. The hyperparameters for the proposed learning model, along with the reproducibility settings, are summarized in Table 2.

3.2. BER performance vs. K-factor (LOS/NLOS conditions)

In the first simulation, we evaluated the performance of an MC-CDMA system employing three commonly used spreading codes: Gold, Hadamard, and Zadoff–Chu, under varying Rician fading conditions with different K-factors: 0 dB, 5 dB, and 10 dB. The Rician fading model represents a realistic wireless channel that includes LOS and NLOS components. In this context, a lower K-factor indicates more severe fading; notably, $K = 0$ dB corresponds to Rayleigh fading, which represents the most detrimental case with no LOS component. We compare the proposed method and the baseline method OTFS.

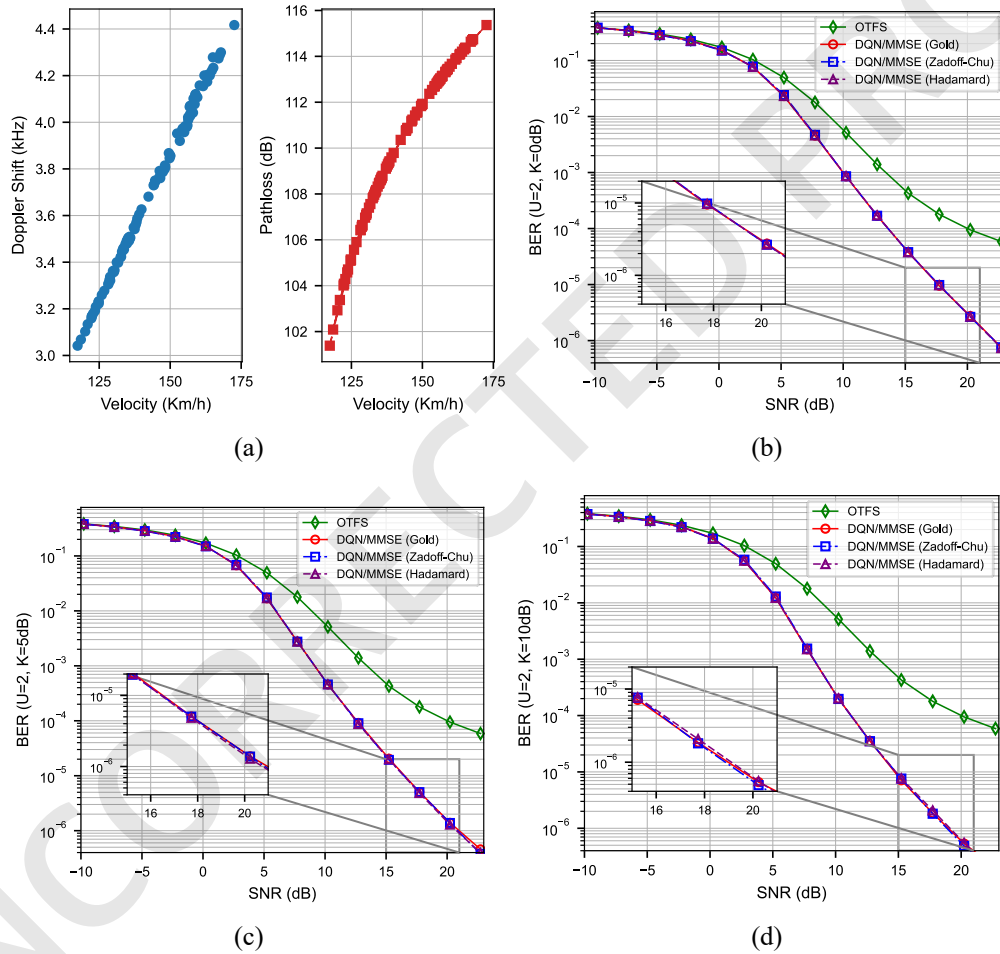


Figure 3. (a) Doppler shift characteristics from the IDM + Markov lane-change mobility model; (b) BER vs. SNR for $U = 2$, $K = 0$ dB (Rayleigh fading), Zadoff–Chu outperforms Gold and Hadamard; (c) BER vs. SNR for $U = 2$, $K = 5$ dB, performance improves with partial LOS; (d) BER vs. SNR for $U = 2$, $K = 10$ dB, strong LOS yields the lowest BER across all codes, with ZC best.

Figure 3(a) presents the characteristics of Doppler shift in realistic vehicular environments using the IDM for longitudinal motion and a Markov chain-based lane-changing model for

lateral dynamics. Figures 3(b-d) shows a significant impact of the K-factor on system performance. When $K = 0$ dB, the BER is the highest across all spreading codes due to the dominance of multipath fading. As the K-factor increases to 5 dB and 10 dB, the presence of a stronger LOS component effectively mitigates fading effects, resulting in a substantial decrease in BER across the SNR range. This improvement is particularly evident in the low to moderate SNR region (0–15 dB), where the impact of fading is most pronounced. In terms of spreading code performance, Zadoff–Chu code consistently outperforms the other codes due to its constant amplitude and ideal correlation properties, which effectively minimize multiple access interference (MAI). Hadamard codes also demonstrate good performance, provided that the number of users does not exceed the code length ($U \leq N$). On the other hand, Gold codes yield higher BER due to their less favorable cross-correlation characteristics, especially under increased user density.

3.3. BER performance vs. number of users

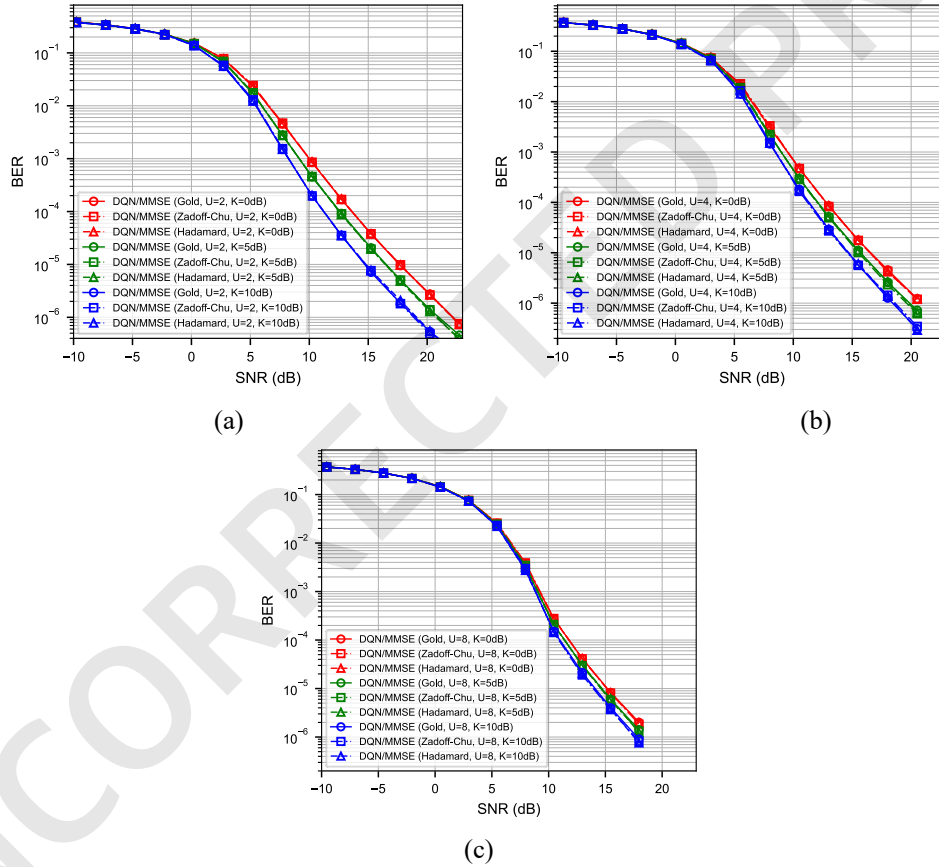


Figure 4. BER performance comparison at a number of users and various Rician fading: (a) $U = 2$; (b) $U = 4$; and (c) $U = 8$. Zadoff–Chu maintains lower BER under high user load, showing better scalability and robustness than Gold and Hadamard codes.

Next, we evaluated the impact of MAI on the performance of the proposed algorithm with three kinds of spreading codes Gold, Hadamard, and Zadoff–Chu. Figure 4 demonstrates that increasing the number of users from 2 to 8 leads to a clear degradation in BER due to higher

MAI. However, this performance drop is considerably smaller for Zadoff–Chu codes, highlighting their scalability in multi-user environments. Compared to the baseline OTFS scheme, the proposed MC-CDMA system combined with ZC codes significantly outperforms, especially in heavy fading and high-user scenarios. The results confirm that the Zadoff–Chu spreading code, combined with Doppler estimation and MMSE filtering, provides the most robust solution for reliable communication over Rician fading channels, particularly under challenging conditions with little or no LOS.

3.4. Impact of multi-user detection schemes (ZF vs. MMSE)

After presenting the main BER trends, we now examine the effect of detection schemes by comparing the performance of the system under two linear multiuser detection techniques: ZF and MMSE. Two distinct channel and user-load scenarios are considered to highlight the impact of fading severity and multiple access interference.

Figure 5 illustrates that with a lightly loaded system ($U = 2$) and a strong LOS condition ($K = 10$ dB), both ZF and MMSE achieve low BER across the SNR range. The performance gap between ZF and MMSE is minimal, as the channel matrix is well-conditioned and noise is the dominant factor. This confirms that ZF is sufficient in favorable propagation environments with low interference. In contrast, the second scenario with higher user density ($U = 4$) and no LOS component ($K = 0$ dB) reflects a severe Rayleigh fading environment with strong multiuser interference. Under these conditions, ZF suffers from performance degradation due to noise enhancement and ill-conditioned channel inversion. Meanwhile, MMSE maintains significantly lower BER, benefiting from its noise- and interference-aware filtering. This demonstrates the superior robustness of MMSE in challenging multi-user fading scenarios.

In summary, while ZF performs well in ideal conditions, MMSE consistently provides more reliable detection, particularly in dense, fading-intensive environments. The comparison underscores the importance of selecting an interference mitigation strategy that adapts to both channel statistics and network load.

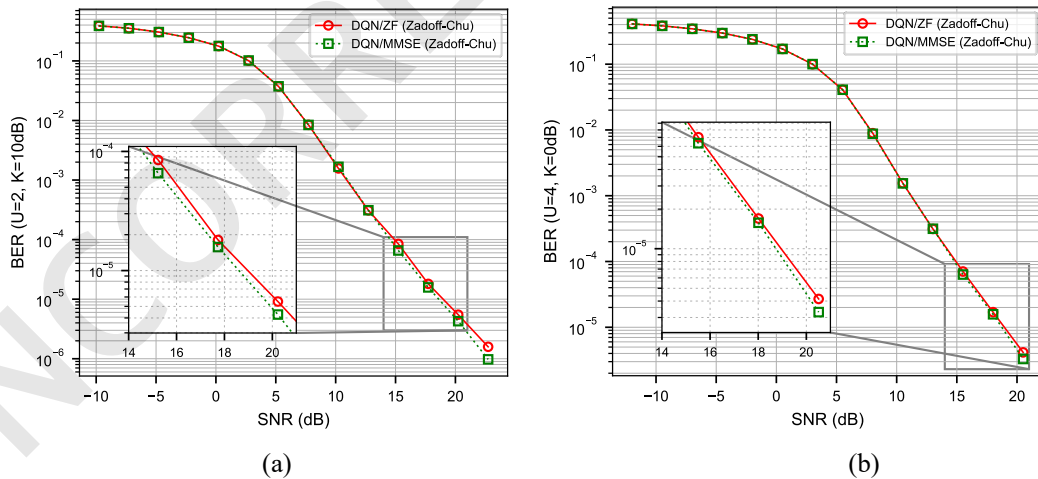


Figure 5. BER performance comparison between ZF and MMSE under different fading and user density scenarios: (a): $U = 2$, $K = 10$ dB, both achieve low BER; ZF suffices under favorable channel conditions; (b): $U = 4$, $K = 0$ dB, MMSE significantly outperforms ZF in heavy fading and high MAI conditions.

3.5. DQL training behavior and throughput analysis

The DQL agents are trained for 1000 episodes (160,000 steps, 160 steps each) using an ϵ -greedy policy (ϵ decays from 1.0 to 0.05 over 50k steps), Xavier uniform initialization, and fixed seeds for Python/NumPy/PyTorch/CUDA (12345) with cuDNN deterministic mode enabled. Key hyperparameters are listed in Table 2.

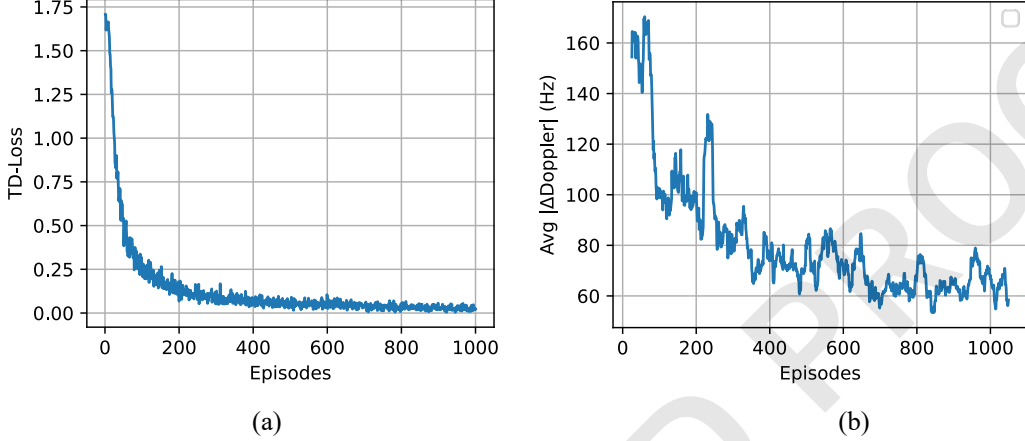


Figure 6. DQL training behavior: (a) Temporal difference (TD) loss; (b) Doppler estimation error.

Convergence analysis in Figure 6(a) shows that the TD loss decreases steadily to a low stable value as the post-detection SINR improves and stabilizes, confirming the effectiveness of the learned policy. Figure 6(b) shows the evolution of Doppler Estimation Error with the number of training episodes in the V2X scenario with Rician fading channel. The results show that the Doppler estimation error tends to decrease gradually with the training time, proving that the reinforcement learning model has exploited the vehicle dynamics and channel characteristics to optimize the estimation process. After about 400 episodes, the curve gradually converges and maintains a stable low error level. This shows that the improved DQN algorithm together with the reasonably designed reward has helped the system adapt faster to the Doppler.

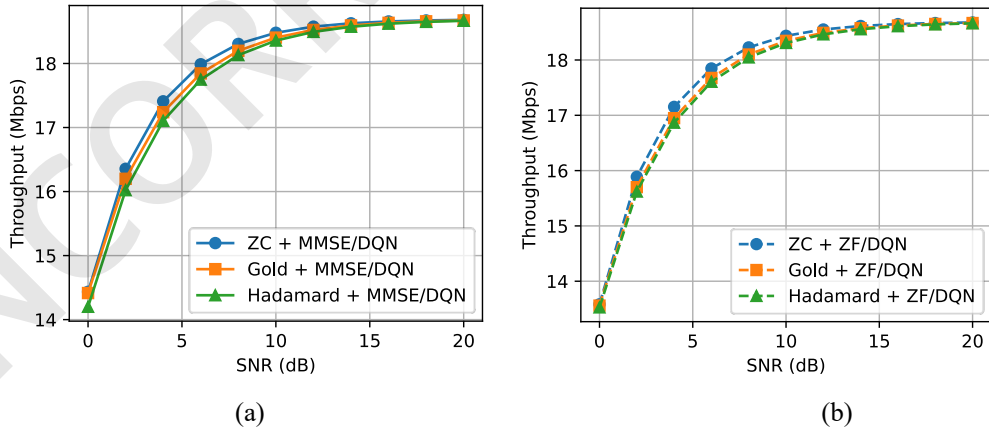


Figure 7. Throughput vs. SNR (a) Comparison among Zadoff–Chu, Gold, and Hadamard spreading codes at $f_c = 12$ GHz, $BW = 10$ MHz. ZC+MMSE/DQN achieves the highest throughput across SNRs; (b) with ZF detection, all codes exhibit lower throughput than MMSE/DQN.

We evaluate the achievable throughput of the proposed multi-user MC-CDMA-OTFS V2X system under different spreading codes (Gold, Hadamard, and Zadoff-Chu) and detectors (ZF/MMSE with DQN-based Doppler tracking). Figure 7 shows that MMSE/DQN consistently outperforms ZF, especially in the low-to-moderate SNR regime where interference and Doppler-induced distortion dominate. The DQN-based Doppler compensation stabilizes the effective SINR, enabling earlier switching to higher MCS levels and thus higher throughput. Zadoff-Chu (ZC) yields the highest throughput, followed by Gold and Hadamard. The constant-amplitude and superior correlation properties of ZC reduce multi-user interference after despreading, which translates into a noticeable throughput gain across the SNR range.

4. CONCLUSIONS

In this paper, we have proposed a novel hybrid communication framework that integrates the strengths of MC-CDMA and OTFS with a Multi-Agent Deep Q-Learning algorithm for mobility-aware channel tracking. By combining multi-user spreading and delay-Doppler domain processing, the system learns to adaptively update channel estimates and Doppler compensation strategies in real-time. Simulations were conducted for proposed algorithm under challenging conditions, including Rician fading with varying K-factors, non-orthogonal spreading codes (e.g., Gold code), and stochastic multi-user interference. The results demonstrate that in ideal scenarios, such as low user density and strong Line-of-Sight ZF achieves satisfactory performance due to well-conditioned channel matrices and low interference. However, as the environment becomes more complex, particularly in fading-dominant conditions with more user's performance degrades significantly, DQN-based approaches prove more resilient, showing improved adaptability and reduced BER thanks to their learning-based optimization of Doppler compensation.

Importantly, the choice of spreading code plays a pivotal role. Zadoff-Chu and Hadamard codes maintain orthogonality under mobility and offer superior performance over Gold codes, especially when the number of users increases. MMSE detection further enhances system robustness by balancing interference suppression and noise resilience, particularly under Rayleigh fading. In contrast, ZF becomes prone to noise amplification when channel matrices are ill-conditioned. The proposed framework effectively balances complexity, adaptability, and robustness, making it a promising solution for intelligent IoV systems operating under highly dynamic wireless conditions. This enables scalable, reliable communication for future 6G vehicular networks.

In our future work, we aim to extend the current study by integrating multi-agent DQN with MIMO-based beamforming and intelligent spreading code adaptation. Furthermore, the DQN framework will be trained on real-world data to enable practical system deployment, with continuous learning capabilities in time-varying vehicular networks. To address synchronization errors and Doppler-induced ICI, we will investigate MIMO-enabled MC-CDMA enhanced with advanced synchronization and channel estimation methods, thereby improving robustness in dynamic 6G-V2X environments. These research directions are expected to significantly enhance the reliability and efficiency of communication systems under complex and rapidly changing conditions, particularly in 6G-enabled IoV scenarios.

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Declaration of competing interest. The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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