

RIMA-HO: Radio Interface Management Approach for Handover Optimization in Heterogeneous C-ITS Environments

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Abstract— Micromobility services such as e-scooters and bicycles are increasingly integrated into Cooperative Intelligent Transportation Systems (C-ITS) through heterogeneous Internet of Vehicles (IoV) architectures. However, frequent signal-strength-based handovers in dense 5G deployments lead to latency increase, packet loss, energy drain, and network congestion. This paper proposes Radio Interface Management Approach for Handover Optimization (RIMA-HO), an intelligent handover framework based on offline reinforcement learning using Conservative Q-Learning (CQL). The proposed approach jointly considers RF quality, latency, Packet Delivery Ratio (PDR), battery level, and congestion to derive adaptive and energy-aware handover decisions. Evaluations on a realistic V2X dataset show a reduction of unnecessary handovers up to 41.8%, with an average reduction of 16.3% compared to conventional quality of signal-based strategies, while preserving QoS constraints. These results demonstrate the potential of offline learning for safe and reliable handover control in micromobility-oriented C-ITS environments.

Keywords— *Micromobility, IoV, C-ITS, handover management, reinforcement learning.*

I. INTRODUCTION

Micromobility modes, including bicycles and electric scooters, are increasingly adopted in urban environments due to their health, economic, and environmental benefits, offering light, flexible, and sustainable transport solutions [1]. As vulnerable low-speed road users, micromobility entities require continuous, reliable connectivity with surrounding vehicles and infrastructure to operate safely. Their integration into Intelligent Transportation Systems (ITS) is therefore essential [2]. C-ITS have emerged as a key technological paradigm to address critical challenges in modern urban mobility [3]. C-ITS relies on Vehicle-to-Everything (V2X) communication within heterogeneous Internet of Vehicles (IoV) architectures that combine Dedicated Short-Range Communications (DSRC) and 5G networks to enable real-time message exchange. These technologies ensure strict Quality-of-Service (QoS) requirements for safety-critical and mobility-oriented

applications [4]. Cooperative Awareness Messages (CAMs) and Decentralized Environmental Notification Messages (DENMs) serve as core mechanisms in C-ITS for the real-time dissemination of vehicle status data and hazard notifications [5],[6].

The integration of micromobility into heterogeneous IoV-based C-ITS environments significantly increases the necessity of intelligent radio interface management in dense dynamic urban scenarios. In particular, 5G networks depend on dense small-cell deployments and high-frequency mmWave bands. These bands exhibit pronounced sensitivity to blockage, severe path loss, limited diffraction, and fast temporal variations in signal quality due to dynamic mobility patterns challenges that exacerbate handover frequency and degrade overall reliability in micromobility-integrated vehicular scenarios [7].

However, many related works concerning radio interface selection and handover mechanisms mainly rely on signal quality indicators and require continuous online interaction. Signal-based decision strategies [8],[9],[10] are not suitable for sensitive real case scenarios and often result in inefficient and unstable transitions, such as ping-pong effects and failed operations. These inefficiencies critically degrade network performance metrics, namely: increased end-to-end latency, reduced PDR, elevated energy consumption (particularly critical for battery-constrained micromobility devices), and intensified network congestion arising from frequent handover signaling and resource contention. These signal-driven approaches overlook user-centric contextual information such as battery level, mobility speed, and traffic load conditions, which are critical for vulnerable and low-power micromobility devices requiring permanent and energy-efficient connectivity. In addition, existing handover approaches are mainly designed and evaluated for high-speed vehicular scenarios [8], [9], [10] and do not explicitly address the specific mobility patterns and constraints of micromobility users with different requirements.

These limitations clearly highlight the need for an intelligent and adaptive handover mechanism capable of jointly optimizing

multiple performance metrics rather than relying solely on radio signal strength.

To address these challenges, this paper proposes RIMA-HO, a Radio Interface Management Approach for Handover Optimization in heterogeneous C-ITS environments integrating micromobility. It relies on Offline Reinforcement Learning using the Conservative Q-Learning (CQL) algorithm to make proactive and intelligent radio interface selection. Multiple metrics, including Radio Frequency (RF), latency, PDR, battery level, and network congestion, are jointly considered to ensure seamless and energy-efficient connectivity. The proposed RIMA-HO mechanism is evaluated using realistic V2X datasets in 5G-supported environments. So, the main contributions of this work are as follows:

- A multi-metric handover decision framework for micromobility C-ITS environments.
- An Offline Reinforcement Learning-based conservative handover optimization using CQL.
- An energy-aware and congestion-aware decision policy for improved network efficiency.
- An evaluation under heterogeneous 5G/ITS-G5 (DSRC) communication conditions.

The results demonstrate a significant reduction in unnecessary handovers and notable improvements in overall network performance compared to conventional handover schemes. This work focuses on vertical handovers between 5G NR and ITS-G5 (DSRC), as micromobility devices face distinct blockage challenges in mmWave bands. However, our framework can also accommodate horizontal handovers between 5G cells by extending the state space with neighboring cell measurements. For clarity, in the remainder of this paper, “handover” refers to vertical handover unless explicitly stated otherwise. The degradation scenarios in Section III primarily target conditions where 5G link quality deteriorates, making DSRC a viable alternative.

This paper is structured as follows: Section II introduces the system model. Section III presents and discusses the performance results, demonstrating the effectiveness of the proposed RIMA-HO solution. Finally, Section IV concludes the paper and outlines future research perspectives.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. System Architecture

This proposed system considers a heterogeneous IoV architecture designed for micromobility scenarios, integrating both 5G New Radio (NR) and ITS-G5 (DSRC) communication technologies. As illustrated in Figure 1, the system comprises On-Board Units (OBUs) on micromobility devices, Roadside Units (RSUs), and 5G base stations (gNodeBs), supervised by a RAN Intelligent Controller (RIC). The RIC's role is to supervise network conditions, manage resources, and enable intelligent control and service orchestration. Micromobility entities primarily rely on 5G cellular connectivity for wide-area connectivity and can additionally exploit DSRC links for short-range V2V and V2I communications. While equipping

micromobility devices with both 5G and DSRC radios incurs additional hardware costs, several factors mitigate this concern:

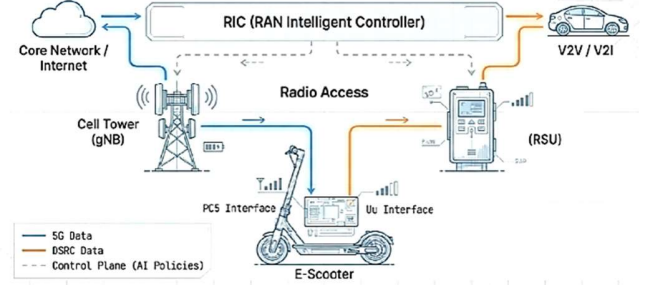


Fig. 1. System Model

- (i) Modern V2X chipsets integrate both technologies on a single die with a shared RF front-end, reducing the incremental cost;
- (ii) DSRC radios consume <100 mW in listening mode, representing <5% of a typical e-scooter battery budget for communication;
- (iii) Many cities already mandate DSRC for V2I safety [11] [12]. RSUs are deployed along urban roads to support cooperative message exchanges (CAM) [13], while 5G base stations provide high throughput and ultra-reliable low-latency communication (URLLC) [14].

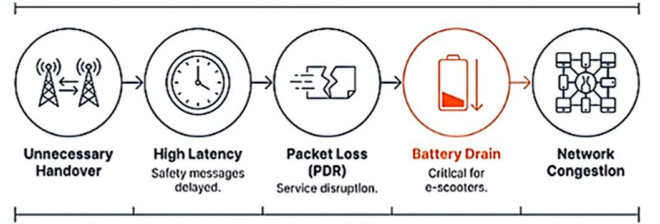


Fig. 2. The chain of failure due to unnecessary handover

Figure 2 illustrates the chain of failures caused by unnecessary handovers: increased latency delays safety messages, packet loss disrupts geofencing and remote locking, accelerated battery drain reduces fleet operational time, and cumulative signaling load intensifies network congestion. For the proposed handover, vertical handover decisions from 5G to DSRC are triggered only when DSRC links provide better communication conditions in terms of reliability and satisfy the imposed QoS requirement. By selectively switching to DSRC when it becomes more suitable, the proposed strategy reduces blockage probability, preserves service continuity, and prevents excessive and inefficient handover operations.

B. Conservative Q-Learning (CQL)

Offline Reinforcement Learning (Offline RL) aims to learn an optimal decision policy from a fixed and pre-collected dataset without any direct interaction with the environment. This property makes it particularly suitable for wireless communication systems, where unsafe exploration and frequent handover actions may severely degrade Quality of Service (QoS) [15]. In this work, we adopt CQL, a model-free Offline RL algorithm that introduces a conservative regularization term in order to mitigate extrapolation errors and constrain the learned policy to remain close to the data distribution. The proposed

approach relies on exploiting multiple network and radio performance indicators extracted from the "AI-Driven Cross-Layer Wireless Network" dataset [16] to determine when a handover is truly necessary. The dataset consists of simulated measurements designed to emulate realistic 5G wireless network behavior, including Radio Frequency (RF) quality, PDR, latency, battery level, network congestion, and user speed. These features are directly mapped to the Conservative Q-Learning (CQL) state variables to ensure consistency between the learning model and the dataset structure. Prior to training, categorical attributes are encoded into numerical representations, and continuous metrics are normalized to ensure comparable value ranges and improve learning stability. No interaction with the communication environment is performed during training. The CQL agent learns exclusively from the fixed offline dataset, and no online exploration or policy update is performed during deployment.

Algorithm 1: CQL-Based Offline Handover Decision

```

// Input and output definition
Input : Offline dataset  $D$ 
Output : Binary handover decision (0: Stay, 1: Handover)
// Data preprocessing
1. Encode RF quality and congestion levels
2. Normalize latency, PDR, and battery metrics
3. Filter low-speed users ( $v \leq 25 \text{ km/h}$ )
// State and action spaces
4. Define the state vector:  $(qRF, p, l, b, c, v) \in \mathbb{R}^6$ 
5. Define the action space:  $A = \{0: \text{Stay}, 1: \text{Handover}\}$ 
// Degradation scenario construction
6. Define degradation criteria:
 $C = \{\text{Low Battery}, \text{High latency}, \text{Low PDR}, \text{Medium} / \text{high congestion}\}$ 
7. Generate degradation scenarios by combining RF Poor with
subsets  $C_k \subseteq C$ 
8. Identify critical states using :
 $1_{crit}(s) = 1$  if RF Poor and at least one additional degradation
criterion is satisfied,
0 otherwise,
// Offline transition and reward construction
9. Extract transitions  $(s, a, r, s')$  from the offline dataset
10. Compute the reward :
 $R(s, a) = \alpha 1_{crit}(s) - \beta a + \gamma Q_{good}(s)$ 
11. Store the resulting transitions in the offline training set
// Offline CQL learning
12. Initialize the CQL model
13. Train the CQL model exclusively on the fixed offline dataset
14. Learn the Q-function using the CQL objective
15. Apply conservative regularization to reduce overestimation of
poorly represented or unseen actions in the offline dataset
16. Obtain the learned handover policy from the trained model
// Handover decision
17. For a given state  $s$ , evaluate the available actions using the trained
CQL model
18. Select the action with the highest learned action value.
19. if selected action = 1 then
20.   HandoverTrigger  $\leftarrow 1$ 
21. else
22.   HandoverTrigger  $\leftarrow 0$ 
23. end if
24. return HandoverTrigger

```

DSRC availability is synthetically generated based on distance to RSUs (<300 m) and RF conditions, following

established heterogeneous network evaluation methodologies [17]. In the context of micromobility scenarios, where channel and network conditions dominate the decision process, the system state is constructed as a multidimensional vector integrating physical-layer and network-layer information derived from the processed data. Different degradation scenarios are generated by combining poor RF conditions with additional quality-of-service constraints in order to reflect realistic adverse network situations that may trigger excessive handover events. These scenarios are constructed through a weighted aggregation of criteria, defined as $\sum_i w_i f_i(S)$, where w_i denotes the relative importance of each metric and $\sum_i w_i = 1$. This dataset-driven formulation enables safe Offline RL training and allows the CQL agent to learn a conservative and stable handover policy. An MDP is defined by the tuple (S, A, P, R, γ) where: S is the state space, A is the action space, $P(s'|s, a)$ is the transition probability from state s to state s' after taking action a , $R(s, a)$ is the immediate reward function, $\gamma \in [0, 1]$ is the discount factor. The system state at each time step integrates information from the "AI-Driven Cross-Layer Wireless Network" dataset. After preprocessing (encoding categorical variables and normalizing continuous quantities), the state is represented by a multidimensional vector including:

- RF quality (qRF): indicator of the radio link quality.
- PDR (p): proportion of successfully received packets.
- Latency (l): transmission delay.
- Battery level (b): remaining energy of the terminal.
- Network congestion (c): indicator of network load.
- User speed (v): movement speed, low speeds are filtered to consider only micromobility).

Thus, the state is $(qRF, p, l, b, c, v) \in \mathbb{R}^6$. These variables are chosen because they capture both radio conditions, Quality of Service (QoS), and energy constraints, which are essential for vulnerable micromobility users. The action a is binary: $a = 0$ stay connected to 5G (no handover), and $a = 1$ trigger a vertical handover to the DSRC network. In the offline reinforcement learning setting, the transition dynamics are not explicitly modeled. It is assumed that transitions between states are Markovian and can be extracted from the dataset, which contains temporal sequences of states and actions. The reward should reflect the handover objectives: minimize user exposure to degraded conditions (critical combinations) while avoiding unnecessary handovers. We propose a composite reward with three terms:

$$R(s, a) = \alpha 1_{crit}(s) - \beta a + \gamma Q_{good}(s) \quad (1)$$

- ✓ $1_{crit}(s)$: indicator that equals 1 if the state corresponds to a critical combination (poor RF AND at least one other degraded criterion: high latency, low PDR, low battery, high congestion). This penalty pushes the agent to avoid these states.
- ✓ a : unit cost for each handover performed. Thus, the agent learns not to handover unnecessarily.

- ✓ $Q_{good}(s)$ positive reward when the state is good (good RF AND all other indicators within acceptable ranges compared to thresholds).
- ✓ α, β, γ are coefficients to be adjusted (large α to heavily penalize critical states, moderate β to discourage handovers, small γ to reward good states).

The condition "RF Poor plus additional criterion" is captured by $1_{crit}(s)$. The QoS improvement check is implicit: handover costs β so the agent will only choose it if it allows escaping a critical state. The probability threshold (handover probability) is not directly modeled; it is the learned policy that will determine, based on Q-values, when to handover. In the offline learning setting with CQL, the transition dynamics are not explicitly modeled. Transitions (s, a, r, s') are extracted from the dataset. The algorithm learns the Q-function from these transitions without interacting with the environment. The agent seeks a policy $\pi(a|s)$ that maximizes the expected discounted cumulative reward:

$$J(\pi) = E \left[\sum_{t=0}^{\infty} \gamma^t R(s_t, a_t) \right] \quad (2)$$

This corresponds to minimizing exposure to critical states while avoiding unnecessary handovers, exactly as the rule-based algorithm does. The CQL algorithm uses the dataset to learn the Q-function by adding a conservative regularization term. This regularization ensures that the learned policy does not overestimate the values of rare or absent actions in the data, which is crucial to avoid risky handovers. The resulting policy will therefore be conservative: it will handover only when the data shows that it leads to a reliable improvement, which aligns well with the spirit of the described algorithm. The overall handover decision procedure as illustrated in Algorithm 1. Although the dataset is not collected from a real vehicular deployment, the selected features (RF quality, latency, congestion, PDR, battery level) are representative of heterogeneous V2X communication conditions and allow controlled evaluation of intelligent handover policies in micromobility-oriented C-ITS environments.

III. RESULTS

The obtained results demonstrate that the proposed solution achieves promising performance in terms of handover reduction and communication stability. To further highlight the effectiveness of the proposed RIMA-HO approach, its performance is subsequently compared with baseline handover strategies commonly adopted in related works. The proposed RIMA-HO framework is evaluated on 1183 micromobility samples ($v \leq 25$ km/h [18]) extracted from a 5000 sample V2X dataset. Each sample corresponds to a vehicle periodically transmitting a CAM message every 100 milliseconds (10 Hz) over a 5G network. The feature set used to construct degradation scenarios includes RF link quality, PDR, end-to-end latency, battery level, and network congestion. These metrics were selected due to their direct impact on communication reliability and handover performance in V2X systems. A minimum acceptable PDR value of 95% was adopted in accordance with the reliability requirements of safety-related V2X services [19],

ensuring a sufficiently high probability of successful message delivery. An upper bound of 100 ms was imposed on end-to-end latency to comply with the strict delay constraints of CAM transmissions supporting time-critical cooperative awareness applications. A lower bound of 20% on battery level was considered to characterize energy-critical operating conditions in which frequent handover operations may further degrade device lifetime and system stability [20]. Network congestion states were restricted to medium and high levels in order to capture scenarios associated with increased channel load and packet contention. Seven degradation scenarios (C1–C7) are constructed by combining poor RF with one or more additional impairments (low PDR, low battery, medium/high congestion), as summarized in Table I.

TABLE I. Degradation scenarios

Criteria	C1	C2	C3	C4	C5	C6	C7
RF Poor	1	1	1	1	1	1	1
PDR $\leq 95\%$	1	0	1	0	1	0	1
Battery $\leq 20\%$	0	0	0	1	1	1	1
Latency ≥ 100 ms	0	0	0	0	0	0	0
Congestion High/Medium	0	1	1	0	0	1	1

Latency does not reach the 100 ms threshold in the dataset used, possibly due to the filtering of low-speed vehicles from the dataset. Nevertheless, it is incorporated into the model as a safety trigger, activated as a last resort when the other criteria are insufficient to discriminate between the available decisions. Note that the single-criterion RF-poor case is excluded, as it does not allow discrimination between samples and therefore yields no optimization gain. In addition, Figure 3 presents the normalized handover urgency scores associated with each scenario, representing the urgency of triggering a handover.

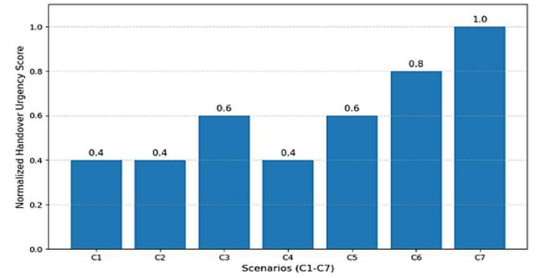


Fig. 3. Normalized Handover Urgency Scores Across Degradation Scenarios

High-score scenarios (C6 and C7, 0.8–1.0), where multiple critical conditions such as packet loss and congestion coexist with low battery level, require immediate handover execution to avoid service degradation, whereas low-score scenarios, where network performance remains acceptable, indicate that handovers should be avoided to prevent unnecessary signaling overhead and battery consumption. The matrix highlights that packet loss (PDR $\leq 95\%$) and congestion are dominant factors in critical scenarios (C3, C6, C7) and should therefore be assigned higher weights in decision algorithms, while low battery level ($\leq 20\%$) becomes a decisive parameter from scenarios C4 to C7, motivating handover optimization toward

more energy-efficient connections. The latency criterion ($\text{Latency} \geq 100$ ms) is not activated in the evaluated scenarios, indicating that the considered degradation situations are mainly driven by packet loss, congestion, and battery constraints. Each scenario corresponds to a specific combination of conditions that enables scenario-based handover policies, such as redirecting users to less loaded cells in packet-loss and congestion cases (example C3), prioritizing energy efficiency in battery-critical situations (C4 to C7), and ensuring service continuity under multi-criteria degradation. Furthermore, the proposed matrix helps avoid ping-pong effects by defining a minimum necessity threshold for handover execution and supports battery-aware strategies for micromobility devices by limiting handovers when energy is scarce unless performance degradation becomes critical. In addition, the normalized scoring mechanism presented in Figure 3 enables dynamic decision-making by assigning real-time urgency values to each criterion combination and triggering handovers only when the global score exceeds a configurable threshold, while prioritizing devices with the highest urgency levels. Based on the combinations defined in Table I, the corresponding occurrence percentages are reported in Figure 4.

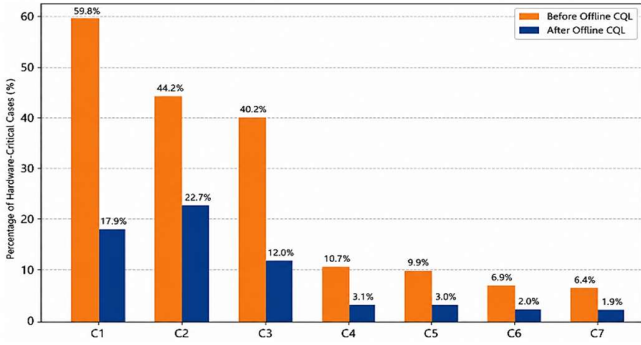


Fig. 4. Percentage of handover-critical cases before and after applying the proposed offline CQL-based handover optimization approach. “Before CQL-based optimization” represents the percentage of handover-critical cases before applying the proposed approach, whereas “After CQL-based optimization” represents the percentage remaining after applying the proposed approach across scenarios C1–C7

The orange bars represent the handover-critical cases obtained with the conventional handover decision strategy before Offline CQL optimization, which serves as the baseline under the same dataset and simulation conditions. The blue bars represent the corresponding cases after applying the proposed RIMA-HO policy. Since both approaches are evaluated on the same 1183 samples and under the same degradation scenarios, this comparison directly quantifies the impact of the proposed Offline CQL-based optimization. The results show a significant reduction in handover-critical cases across all degradation combinations while preserving the required QoS constraints in terms of PDR and end-to-end latency. Additionally, this leads to improved energy efficiency, since handover procedures introduce additional signaling and transmission overhead. The integration of battery level into the decision process enables energy-related constraints to be explicitly considered and promotes energy-efficient handover strategies. All results

demonstrate the ability to discriminate between efficient and inefficient handover events in complex multi-metric operating conditions.

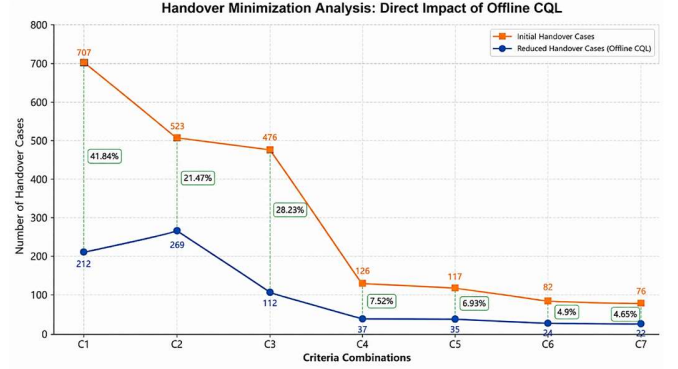


Fig. 5. Handover Improvement Percentage

Figure 5 illustrates the comparison of unnecessary handovers before and after applying the proposed CQL policy under different criteria combinations, demonstrating the resulting improvement. The results reveal a substantial reduction in unnecessary handovers, with a maximum reduction of 41.84% achieved for the best-performing criteria combination (C1) and an average reduction of approximately 16.35% across all evaluated combinations. Table II presents five representative examples of handover-critical vehicle samples collected at different time instants before and after applying the proposed RIMA-HO policy, where the number of handovers decreases from 9 to 3, corresponding to a reduction of approximately 66.7%. All retained cases satisfy the QoS constraints defined in this study, with a PDR exceeding 95% and end-to-end latency remaining below 100 ms. Furthermore, Shannon capacity was evaluated to assess channel availability under varying network conditions. The measured throughput values, extracted from the dataset (Throughput (Mbps)), remain consistently below the estimated Shannon capacity values (Shannon_Capacity ((Mbps)), which were calculated from the corresponding SNR measurement (SNR (dB)). This confirms that the required transmission demand remains within the achievable channel capacity limits after handover optimization, while the QoS indicator remains equal to 1 (QoS_OK) in Table II, indicating that the defined QoS requirements are consistently satisfied across all retained samples.

TABLE II. Representative examples of handover-critical vehicle samples

Time (s)	SNR (dB)	PDR (%)	Lat. (ms)	HO Before	HO After	QoS
43	7.54	97.65	68.57	2	1	✓
174	9.22	98.41	34.58	3	1	✓
225	9.01	97.64	86.6	1	0	✓
870	6.8	99.49	94.05	1	0	✓
1420	15.57	95.87	47.83	2	1	✓

To further emphasize the positioning of the proposed RIMA-HO approach with respect to existing solutions, Table III presents a comparative analysis of representative related works.

TABLE III. Comparative analysis with related works

Method	HO Reduction / Performance	Metrics Used	Environment
[8] SHS	+7% throughput, -56% latency	SINR, channel	5G mmWave
[9] DQN	Reduced ping-pong (no % reported)	RSRP, SNR, velocity, load	Ultra-dense 5G
[10] CHO	~11% HO reduction, -7% RLF	RSRP, RSRQ, velocity	5G high-mobility
RIMA-HO (proposed)	16.3% avg, 41.8% max reduction	RF, latency, PDR, battery, congestion	Het. 5G + DSRC

For instance, compared to the related work in [10], which optimizes Conditional Handover (CHO) decisions mainly based on radio channel quality indicators (RSRP) and handover performance metrics and reports a handover reduction rate of about 11%, the proposed RIMA-HO approach achieves significantly higher performance gains. The method in [10] relies on a single-layer decision strategy and does not explicitly consider the joint impact of higher-layer and system-level degradation factors such as PDR, battery level, latency, and network congestion. In contrast, RIMA-HO adopts a multi-metric and cross-layer decision framework that integrates these heterogeneous indicators, enabling more accurate handover minimization and explaining the observed improvement over the approach in [10]. Furthermore, the proposed CQL-based policy implements this multi-metric framework within a unified learning-based process and selectively suppresses unnecessary handovers under critical conditions. These results confirm that the proposed Conservative Q-Learning strategy outperforms conventional baselines in handover optimization while preserving communication reliability, a key requirement for safety-oriented V2X services.

IV. CONCLUSION

In this paper, we proposed RIMA-HO, a Radio Interface Management approach for handover optimization in heterogeneous C-ITS environments integrating micromobility. By leveraging Offline Reinforcement Learning with Conservative Q-Learning (CQL), the proposed approach enables intelligent handover decisions beyond traditional signal-based strategies. We validate the feasibility of offline learning for handover control, showing that efficient decision policies can be derived from historical data without continuous online network interaction, making the approach particularly suitable for safety-oriented C-ITS applications. The obtained results show that jointly considering multiple metrics, including radio frequency (RF), latency, PDR, battery level, and network congestion, significantly minimizes unnecessary handover events while preserving Quality of Service (QoS). As future work, the proposed framework can be extended to service-aware handover in 5G by considering the requirements of eMBB, URLLC, and mMTC services. Its integration into intelligent, self-adaptive 6G architectures also represents a promising direction. In addition, coupling the approach with realistic simulators such as OMNeT++ would enable comprehensive evaluation under complex urban mobility conditions.

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