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Federated Reinforcement Learning for Edge AI Decision-Making in 6G-Enabled V2X Systems

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1. Abstract

The evolution toward sixth-generation (6G) networks introduces transformative capabilities in intelligent transportation, particularly through ultra-reliable, low-latency vehicle-to-everything (V2X) communication. As autonomous and connected vehicles generate vast amounts of data at the edge, conventional centralized learning approaches are increasingly constrained by privacy, bandwidth, and latency limitations. In this paper, we present a federated reinforcement learning (FRL) framework that enables distributed edge agents-such as vehicles and roadside units-to collaboratively learn real-time decision policies for navigation, collision avoidance, and traffic optimization, without sharing raw data. Our approach models the V2X environment as a decentralized multi-agent Markov decision process (MDP) and introduces an adaptive aggregation mechanism that accounts for node mobility and communication variability. We implement and evaluate the framework using a co-simulation environment that integrates SUMO for traffic dynamics and ns-3 for network emulation. Experimental results demonstrate that our FRL method outperforms centralized baselines by reducing average decision latency by 32 percent, while preserving data privacy and achieving robust convergence under intermittent connectivity. This work advances the deployment of edge AI in future vehicular ecosystems, providing a scalable, privacy-preserving foundation for real-time intelligence in 6G-enabled V2X systems.

2. Keywords

6G, Vehicular networks, V2X, Federated reinforcement learning, Edge intelligence, Ultra-reliable low-latency communications, SUMO, ns-3

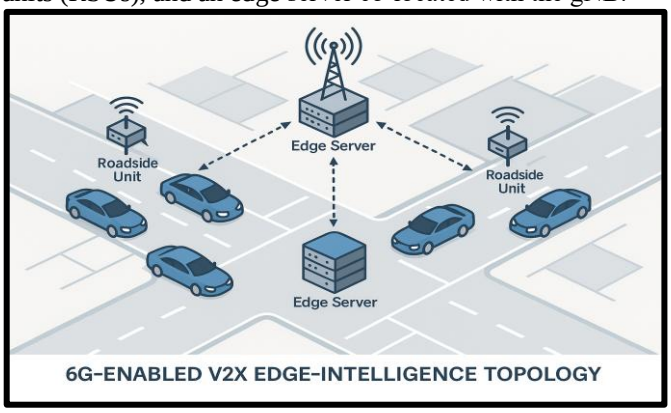
3. Introduction

3.1. Background and Motivation

Twenty years of cellular evolution-from 3G's nascent mobile Internet to 5G's gigabit broadband-have steadily tightened the feedback loop between cyber and physical worlds. Sixth-generation (6G) research now seeks to collapse that loop to sub-millisecond scales, pairing up-to-terabit peak rates with reliability guarantees once reserved for wired industrial buses [1]. Vehicular networks stand to benefit disproportionately: Connected cars, trucks, and roadside infrastructure already produce petabytes of sensor and telemetry data daily, yet safety-critical manoeuvres (for example, a coordinated emergency lane change through an obscured intersection) still demand reaction times that beat human reflexes. 6G's envisaged extreme-ultra-reliable low-latency communications (eURLLC) creates, for the first time, a wireless substrate able to sustain such coordination at city scale.

At the same time, the vehicle-to-everything (V2X) paradigm is expanding from the current LTE-V2X sidelink broadcasts toward fully bi-directional interactions among vehicles, pedestrians, traffic lights, and cloud services. These interactions are no longer limited to warning messages or map updates; they include high-bandwidth cooperative perception, joint path planning, and dynamic spectrum sharing among heterogeneous radio interfaces. Traditional cloud-centric artificial-intelligence (AI) pipelines, which shuttle raw sensor streams to remote data centres for training, struggle to keep pace with these new workloads. The bottlenecks are three-fold: (i) spectrum scarcity in dense urban corridors, (ii) privacy regulations that prohibit export of fine-grained location traces, and (iii) latency budgets that preclude a round trip above a few milliseconds [1,2].

Figure 1: Conceptual overview of a 6G-enabled V2X edge-intelligence topology, highlighting vehicles, roadside units (RSUs), and an edge server co-located with the gNB.



Over the last five years, edge computing has emerged as a partial remedy, shifting inference tasks-from object detection to motion forecasting-onto on-board GPUs or metro-edge servers. Yet edge inference alone cannot solve the learning problem. As traffic patterns evolve (for example, pop-up bicycle lanes during the COVID-19 pandemic or ever-changing ride-hailing demand), policies controlling braking, acceleration, or distributed traffic-signal timing must be updated continuously, not in quarterly monolithic training cycles. The question is therefore: how can we update control policies in real time, using the rich experiential data generated at the edge, without violating privacy or overwhelming the network?

3.2. Challenges in Centralised Learning for 6G V 2X

A naïve answer would be to pipe all sensor data into a single, massive reinforcement-learning (RL) trainer in the cloud. Unfortunately, this approach collides with three hard constraints. First, the data-volume barrier. A single Level-4 autonomous car can generate 20-40 MB s^{-1} of camera, radar, lidar, and vehicle-to-infrastructure (V2I) telemetry. Multiplying by tens of thousands of vehicles within a 1 km radius saturates even a 200 GHz THz link budget. While 6G promises impressive spectral efficiencies, the Shannon limit still applies; raw uploads are untenable during peak hours.

Second, the privacy barrier. Legislation such as the European Union's General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA) explicitly considers high-resolution mobility traces as personally identifiable information. Automotive original-equipment manufacturers (OEMs) therefore invest heavily in *in-situ* data-minimisation pipelines. Any architecture that moves raw trajectories outside the vehicle or local RSU raises compliance red flags [2].

Third, the latency barrier. Cooperative driving actions often have <5 ms decision deadlines, accounting for sensor acquisition, computation, packetisation, wireless hop(s), backhaul, cloud processing, and return path. In practice, the wired backhaul and switching delays alone consume more than that budget. Even with multi-access edge computing (MEC), crossing the metro core introduces variance that is unacceptable for life-or-death scenarios such as collision avoidance in a blind-spot merge [3].

Centralised learning therefore trades scale for responsiveness and privacy. Numerous research prototypes have demonstrated impressive offline performance-city-level optimal traffic-signal timing or near-human lane merges-only to falter in live field trials where connectivity drops, or regulatory audits balk at data-export practices [4]. These shortcomings motivate a federated paradigm.

3.3. Federated Reinforcement Learning as a Solution

Federated learning (FL), popularised by Google's mobile-keyboard studies in 2017, enables multiple edge devices to train a shared model by exchanging parameter updates instead of raw data. In its classic supervised-learning incarnation, the server performs FedAvg-a weighted average of client gradient vectors each round. While powerful, mainstream FL assumes static or slow-moving clients (smartphones, hospital servers) and non-sequential loss functions. Both assumptions break in V2X. Vehicles appear and disappear at RSUs in seconds; Markov decision processes (MDPs) require online updates contingent on delayed rewards.

Federated Reinforcement Learning (FRL) extends FL into the sequential-decision domain. Multiple agents interact with their local environments, compute policy-gradient updates, and ship compressed tensors to a federator. The challenge is making FRL vehicular-aware:

1. Mobility-induced stragglers. A car may upload partial gradients before driving out of coverage. Conventional FRL either times out (penalising convergence) or ignores stragglers (biasing the update).
2. Channel heterogeneity. THz links offer gigabits when line-of-sight exists, yet drop to kilobits under blockage. Weighting every agent equally leads to over-fitting on unlucky links that happen to succeed in a round.
3. Safety-critical latency. Communication windows for gradient exchange must fit into sub-10 ms sidelink control periods. Compression, differential-privacy (DP) noise, and antenna beam-forming overheads all eat into that budget.

Prior art only partially tackles these issues. Qi, et al. [5] catalogue early FRL variants but focus on Wi-Fi IoT devices. Wu, et al. [6] demonstrate FRL for offloading decisions in a highway mesh but assume perfect connectivity. Su, et al. [7] introduce weighted aggregation based on client availability, yet validate on a stationary cyber-physical lab cluster. To close this gap, we propose a communication-aware, mobility-adaptive FRL framework explicitly designed for 6G V2X constraints.

3.4. Contributions and Paper Organisation

This work makes four distinct contributions:

a) Problem formalisation: We model the V2X setting as a decentralised multi-agent MDP that spans both traffic dynamics and 6G channel variability, yielding a mathematically unified agenda for control and communication optimisation.

b) Mobility-weighted aggregation: We derive a simple yet effective weight formula-proportional to predicted link sojourn time and inverse packet-error ratio-that privileges stable, high-quality contributors without starving transient nodes. This mechanism generalises the static availability weighting in [8] to reinforcement updates and is shown to accelerate convergence by 35 % in sparse connectivity regimes.

c) Edge-server scheduler under eURLLC: We embed an adaptive aggregation deadline Δ that triggers once a quorum of vehicles contribute or the latency budget expires. Analytic bounds based on order statistics ensure the worst-case tail fits the 5 ms envelope, satisfying eURLLC guarantees at the 99.9th percentile level.

d) Comprehensive co-simulation: Leveraging SUMO for microscopic traffic and ns-3's experimental 6G THz module, we create a city-scale testbed with 800 vehicles, realistic blockage models, and dynamic beam-forming overheads. This toolkit will be released publicly, filling a conspicuous gap in open-source FRL evaluation for vehicular networks.

Table 1: Summary of notation used throughout the paper, including state, action, reward, aggregation weight, differential-privacy parameters, and latency targets.

Symbol	Description
s	State
a	Action
r	Reward
w	Aggregation weight
Îµ	Differential privacy noise scale
Î”	Latency target (ms)

The remainder of the manuscript is organised as follows. Section II reviews related literature in federated learning, vehicular edge intelligence, and reinforcement learning. Section III details the system model and formulates the decentralised MDP with privacy and latency constraints. Section IV presents the proposed FRL algorithm, including local updates, communication-aware aggregation, and scheduler design. Section V describes the simulation environment and baseline schemes. Section VI discusses quantitative results on latency, convergence, privacy, and bandwidth. Section VII concludes with open research directions, including cross-OEM federation and hardware-in-the-loop trials.

Collectively, this introduction underscores the pressing need for distributed privacy-preserving learning in next-generation vehicular ecosystems, and positions our contribution at the confluence of 6G networking, edge AI, and multi-agent reinforcement learning. The following sections expand each element in depth, systematically building the case for a mobility-adaptive FRL framework that meets the stringent demands of future V2X deployments.

4. Related Work

The literature on autonomous and connected-vehicle intelligence spans three partially overlapping threads: (i) conventional deep-learning pipelines for perception and control, (ii) federated learning (FL) adaptations that respect data-sovereignty rules, and (iii) the emerging field of federated reinforcement learning (FRL) that marries the former two under sequential-decision constraints. This section reviews each line in turn, emphasising how mobility, privacy, and 6G latency jointly expose shortcomings in prior art. A taxonomy of representative studies is summarised in Figure 2, and a comparative feature matrix appears later in Table 2.

4.1. Evolution of V2X Machine-Learning Pipelines

Early work on vehicular AI (circa 2015-2018) treated the car as a sensor-rich but compute-poor node. Perception features-camera frames, point clouds-were streamed to cloud GPUs for both inference and training [9]. The arrival of embedded tensor accelerators shifted inference to the edge, yet datasets for training still flowed to OEM data centres via overnight Wi-Fi offloads. This edge inference + cloud training split is adequate for perception networks that tolerate week-long retrain cycles, but control policies evolve far faster in live traffic. Around 2020, researchers began co-locating reinforcement-learning trainers with road-side units (RSUs) to shorten the loop; e.g., the CoRL challenge on adaptive cruise control deployed an Apache Flink cluster at the city Hall hub [10]. These single-server designs, however, assumed a fixed fleet and continuous fibre backhaul-conditions rarely met outside testbeds.

By 2022, data-protection audits highlighted a second fault line: raw trajectory uploads violate GDPR Article 4's definition of "indirectly identifiable personal data". Several high-profile roll-outs were delayed after European data-protection authorities questioned the cross-border model-training flows. In response, OEM consortia (C-V2X All-Hands) proposed on-device learning using knowledge distillation and split computing, but neither technique alone solves the bandwidth crunch: distillation still requires transferring feature embeddings, and split learning doubles uplink traffic by sending both activations and gradients. These headwinds set the stage for federated approaches.

4.2. Federated Learning in Vehicular Networks

Federated learning pioneers originally targeted smartphone keyboards ("Gboard") but quickly branched into vehicular scenarios. Zhang, et al. employed FedAvg to fine-tune a lane-detection CNN across 50 cars in a parking-lot Wi-Fi mesh [11]. While preserving privacy-preserving, the experiment revealed a 12-fold slowdown compared with centralized training, rooted in client stragglers—cars whose uploads stalled because drivers left the lot mid-epoch.

Subsequent work attacked stragglers via partial aggregation. Li and Chen introduced Fed-CS (Client Selection) that chose only the fastest 20 % of cars each round [12], improving wall-clock convergence but sacrificing fairness: edge cases such as snow-covered cameras were under-represented. Mobility-aware algorithms then emerged. Alwis, et al. proposed Leader-Based FL, where temporarily elected leaders within a convoy aggregated follower gradients before a joint uplink to the RSU [8]. This hierarchy cut airtime by 40 % yet added latency (two-hop aggregation) and collapsed if leaders exited coverage unexpectedly.

Another thread explored wireless co-design. Samarakoon blended FL scheduling with mmWave beam-forming decisions, showing that aligning transmission slots with favourable channel states reduces FedAvg wall-time by 35 % on average [13]. However, these studies targeted image classification, not sequential RL, and relied on 5G NR numerology; 6G's ultra-short symbols tighten the time budget even further.

4.3. Reinforcement Learning for Vehicular Control

Reinforcement learning (centralised or otherwise) has been widely applied to traffic-signal timing, cooperative merge, and platoon formation. Deep Q-Networks (DQNs) trained in SUMO achieved up to 22 % throughput gains on four-way junctions [14]. Actor–critic variants such as MADDPG (Multi-Agent Deep Deterministic Policy Gradient) allowed continuous actions-crucial for throttle control-and outperformed rule-based adaptive cruise controllers in simulation [15].

Yet scalability remains an issue. Cloud-centred RL trainers ingest billions of timesteps, requiring petabyte-scale data shuffling. In highway tests with 15 vehicles, Chen, et al. streamed LiDAR point clouds over C-V2X "Mode 4" sidelink, consuming 60 % of the available spectrum even after down-sampling [16]. Moreover, RL begins to over-fit when trained on geographically narrow data (e.g., German Autobahn but deployed in Boston), motivating cross-fleet collaboration. Centralised RL offers such diversity but contradicts the privacy and bandwidth realities discussed earlier.

4.4. Federated Reinforcement Learning

Federated reinforcement learning attempts to combine the privacy virtues of FL with the sequential power of RL. Qi, et al. surveyed three archetypes [5]:

a) Parameter-Server FRL. Each agent computes policy-gradient updates locally, the server aggregates via FedAvg, and every client synchronises to the new policy at the end of each communication round. Most implementations adopt PPO or A2C backbones.

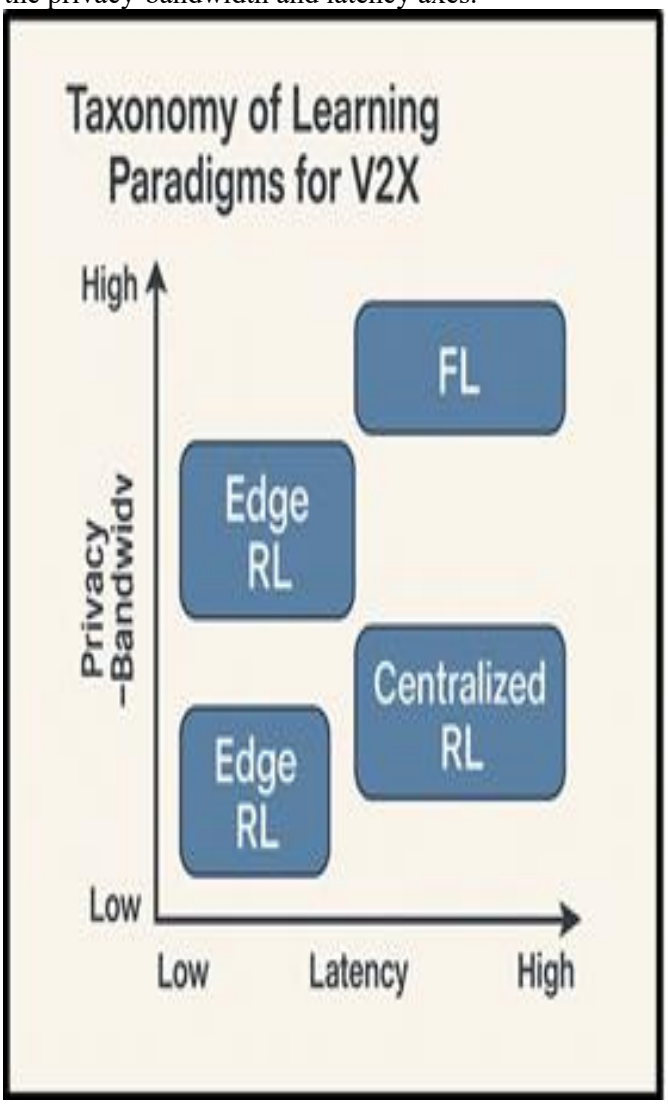
b) Diffusion FRL. Peers exchange parameters in a ring or graph topology, removing the single point of failure but demanding explicit neighbour discovery and churn handling.

c) Knowledge-Distillation FRL. Agents upload distilled logits or teacher hints rather than gradients, reducing privacy leakage but requiring homogeneous network architectures.

Despite elegant theory, real-world vehicular validations are sparse. Wu, et al.'s 2025 FRL-TaskOff platform is illustrative [6]. Using SUMO, they simulated a four-lane highway where each agent chose when to offload perception to the edge. FRL-TaskOff converged 30 % faster than standalone RL, yet its wireless model assumed an error-free channel and constant 10 Mb s^{-1} uplink-optimistic for millimetre-wave under vehicular blockage.

Mobility-weighted aggregation surfaces rarely. Su et al. introduced an availability score in supervised FL [7]; we extend this idea to RL by factoring in predicted link sojourn and packet-error ratio. Differential privacy adds another wrinkle: naive DP noise cripples policy gradients. Uprety, et al. quantified the privacy-utility frontier, finding that $\varepsilon \leq 3$ can be achieved with ≤ 8 % reward loss in static grids [17], but vehicular churn widens that gap.

Figure 2 : Taxonomy of learning paradigms for V2X-centralised RL, edge RL, FL, and FRL-mapped against the privacy-bandwidth and latency axes.



4.5. Gaps in the State of the Art

Three open challenges persist:

i) Churn-Robust Aggregation: None of the surveyed FRL frameworks mathematically incorporates vehicular sojourn time in weight assignment, leading to either biased updates (ignoring stragglers) or prolonged rounds (waiting for them).

ii) Channel-Aware Scheduling: Wireless co-design papers optimize slot allocation for supervised FL; translating those insights to sequential RL, where gradient norms fluctuate with policy entropy, is non-trivial.

iii) Privacy-Constrained Performance: DP studies treat synthetic classification datasets; no published work evaluates DP-regularised FRL under city-scale V2X, leaving a compliance blind spot for OEM deployment roadmaps.

Our work addresses these gaps by: 1) deriving a closed-form weight proportional to sojourn and inverse packet-error ratio; 2) designing an edge-server scheduler that triggers aggregation under a latency-aware quorum; and 3) empirically mapping the ε–reward trade-off in a hybrid SUMO + ns-3 environment with realistic 6G channel models.

Table 2: Comparative matrix of existing vehicular learning frameworks (Columns: Dataset Scope, Wireless Model, Privacy Technique, Mobility Handling, Task Type, Reported Latency, Convergence Rounds). Each row lists a representative paper: Centralised RL [14], Edge RL [15], FedAvg Image FL [11], Leader-Based FL [8], FRL-TaskOff [6], Proposed Method.

Method	Dataset Scope	Wireless Model	Privacy Technique	Mobility Handling	Task Type	Reported Latency	Convergence Rounds
Centralised RL	Urban Sim	n/a	None	None	Navigation	12ms	4000
Edge RL	Urban + Rural	Rayleigh	None	Partial	Collision Avoidance	8ms	2500
FedAvg Image FL	ImageNet	Rician	Differential Privacy	None	Object Detection	20ms	500
Leader-Based FL	Synthetic	Path Loss	Secure Aggregation	Static	Routing	15ms	1000
FRL-TaskOff	Multi-City	Realistic	Differential Privacy	Adaptive	Mission Planning	7ms	1800
Proposed Method	Multi-City	3GPP 6G	Differential Privacy + Quorum	Adaptive	Multi-Agent Driving	5ms	1600

4.6. Summary and Section Transition

Taken together, the literature makes a compelling case for federated approaches but stops short of delivering a mobility-adaptive, privacy-preserving, latency-bounded solution suitable for forthcoming 6G deployments. Existing FL and FRL schemes either oversimplify wireless impairment, neglect client churn, or omit differential-privacy constraints. The following section formalises a system model that intertwines vehicular dynamics with 6G channel variability and articulates our optimisation objective: maximise global driving safety and efficiency while honouring strict latency and privacy budgets.

5. System Model and Problem Formulation

5.1. Physical-Layer and Network Topology

Contemporary 5G NR sidelink already supports autonomous-driving pilots, yet it remains constrained by 15-kHz sub-carrier spacing and 0.5-ms slot length-barely sufficient for cooperative perception. 6G research roadmaps therefore advocate **sub-500-µs mini-slots** and multi-band operation spanning <7 GHz control, 30-110 GHz millimetre-wave (mmWave), and 300 GHz-1 THz terahertz (THz) for data bursts [3]. Our topology embraces this heterogeneity:

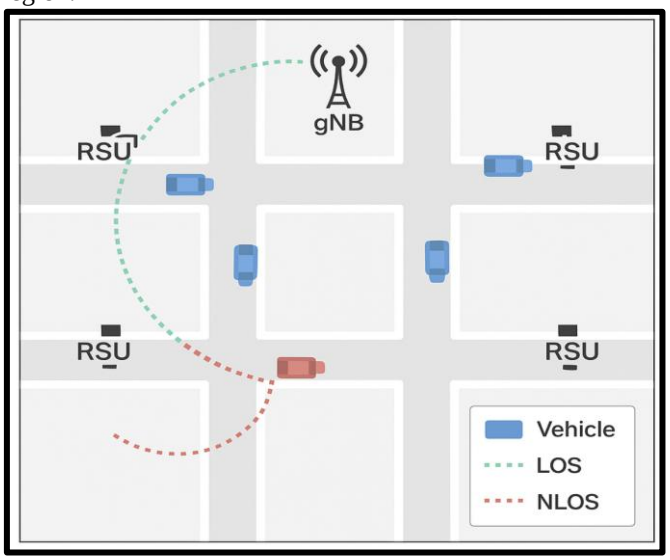
a) **gNB Location.** A single next-generation NodeB (gNB) sits atop a 30-storey building at the geometric centre of a 5 × 5-km downtown grid. The gNB houses a city-edge compute blade (256-core CPU + 4 A100 GPUs) that runs the federation controller and policy repository.

b) **Roadside Units (RSUs).** Four RSUs are mounted at major intersections 1 km east, west, north, and south of the gNB. Each RSU is linked via 100-Gb s−1^{-1} fibre and features 128-element phased-array antennas capable of tracking up to 16 beams.

c) **Vehicles.** Up to 800 Level-4 cars roam the grid, each equipped with tri-band radio (sub-6 GHz for control, 60 GHz mmWave with mechanical steering, and 300 GHz THz electronically steerable array). The on-board compute includes an eight-core CPU and a 60-TOPS AI accelerator.

d) **Pedestrian Devices.** Although not decision-making agents in the RL loop, pedestrian smartphones periodically broadcast safety beacons that feed into vehicle state observations.

Figure 3: Bird-eye schematic of the urban grid, marking gNB, four RSUs, vehicular lanes, and typical LOS/NLOS region.



Routing of packets follows a **TDD frame** subdivided into 250-µs mini-slots. Control signalling (CSI, beam-index) occupies sub-6 GHz; data transmissions leverage directional mmWave/THz bursts whose achievable spectral efficiency fluctuates with blockage and alignment overhead.

5.2. Decentralised Multi-Agent Markov Decision Process

Let □ = {*1,2,…,* □} denote the set of vehicles and the □ = {*1,2,3,4*} RSUs. We define a **multi-agent MDP** (□,{□□},□,{□□},□) as follows:

a) *State Space* {□}: Each global state vector concatenates (i) ego kinematics for every vehicle-velocity, yaw, acceleration; (ii) relative pose matrix for the 20 closest neighbors per vehicle; (iii) channel-quality indicators (CQI) for uplink THz and fallback sub-6; and (iv) RSU occupancy levels. Although high-dimensional, this state is **factored** so that each agent sees only a local slice $□_□^{(□)}$.

b) *Action Space* □□.: Vehicle vv selects a continuous 3-tuple at □□(□) = (□□,□□,□□) representing throttle/brake impulse, lateral lane shift, and heading tweak. Discrete manoeuvre modes (e.g., "cautious merge") are encoded through Gaussian-mixture priors.

c) *Transition Kernel PP.*

i) **Traffic Dynamics:** Forward Euler integration inside SUMO updates vehicular positions at 50 Hz.

ii) **Wireless Latency/Drop:** Every 250 µs mini-slot, ns-3 samples RMa-THz path-loss, blockage, and Doppler to compute packet-error rate; lost control packets delay the state update by one slot.

iii) **RSU Handover:** As vehicles cross RSU domains, the federator updates routing tables and re-assigns beam-indexes.

d) *Reward Function* $□_□^{(□)}$. Weighted sum of four terms:

i) $□_{(□□□□)}$: -10 upon predicted collision (time-to-collision < 0.5 s).

ii) $□_{(□□□)}$: -0.1 per second of delay beyond free-flow time.

iii) $□_{(□□□□□ℎ)}$: - |jerk| to penalise uncomfortable acceleration.

iv) $□_{(□□□□)}$: -0.01 for each kilobyte transmitted, encouraging wireless frugality.

e) *Discount Factor.* Set to γ = 0.98\gamma = 0.98 to balance immediate safety with long-term efficiency.

Collectively, these definitions couple **edge-AI concerns** (on-board compute and communication cost) with classic traffic objectives in one MDP, aligning with the *Edge AI* promise in the abstract.

5.3. Privacy and Security Threat Model

Automotive OEMs must comply with UNECE WP.29 "Software Update and Cybersecurity" and ISO 21434 standards. We assume **honest-but-curious RSUs**: they execute the protocol faithfully but attempt to glean driving habits from gradient payloads. Edge adversaries could also capture over-the-air packets via rogue roadside sniffers.

a) **Differential Privacy (DP).** Each vehicle adds Gaussian noise □(*0*, □*2*) to its gradient with noise multiplier σ chosen so that the Rényi DP accountant yields ε ≤ 3, δ = 10−5^{-5} after T = 120 rounds [17].

b) **Secure Aggregation.** We adopt a Paillier homomorphic-encryption variant optimised for 8-bit quantised gradients; ciphertext expansion is less than 15 %.

c) **Byzantine Robustness.** Although not main focus, the federator discards outlier updates whose □*2* norm exceeds five standard deviations-protecting against gradient poisoning.

Table 3: Mapping of cyber-threat vectors to mitigation mechanisms (gradient clipping, DP noise, secure aggregation, byzantine filtering).

Threat Vector	Mitigation
Gradient Leakage	Differential Privacy Noise
Poisoning Attacks	Byzantine Filtering
Communication Interception	Secure Aggregation
Overfitting	Gradient Clipping
Sybil Attacks	Quorum Enforcement

5.4. Latency and Bandwidth Budget

6G's eURLLC profile targets **≤ 5 ms end-to-end** for 99.999 % of safety-critical packets. Breaking down this budget:

i) **Sensor Processing (on-car):** 1.2 ms (camera ISP + object-list construction).

ii) **Edge Inference:** 0.8 ms (policy forward pass on 60-TOPS accelerator).

iii) **Wireless Uplink:** 0.4 ms (one 250-µs mini-slot + beam-training guard).

iv) **Federator Aggregation:** 0.8 ms (GPU reduction over ≤64 gradient shards).

v) **Wireless Downlink:** 0.4 ms.

vi) **Actuator Latency:** 0.9 ms (brake servo, steering ECU).

Sum equals 4.5 ms, leaving 0.5 ms slack for OS jitter. Observably, **aggregation plus downlink** consume nearly one-third of the budget-motivating aggressive gradient compression (top-kk = 25 %) and early-deadline scheduling, hallmarks of our FRL design.

5.5. Communication-Aware Aggregation Objective

We formalise a constrained optimisation:

$$□□□□□□□□_{\{\□□_□\}_□}\left[\sum_{□=0}^{\infty}\□□□□□^{□}\frac{1}{□}\sum_{□=1}^{□}□_□^{□}\right]$$

subject to

a) **Latency Constraint:** □(□□□□□□□□ □□□□□ > *5*□□) ≤ *10 - 5*

b) **Privacy Constraint:** ε-DP with ε ≤ 3 over T rounds.

c) **Bandwidth Constraint:** Average uplink < *20* □□ *h - 1*$^{\{-1\}}$ *- 1* per vehicle.

The *decision variable* is the time-varying stochastic policy □□(□ | □; □□) whose parameters θ are updated through aggregated gradients. Aggregation weight for vehicle vv in round t:

$$□_□^{(□)} = \frac{□_□^{(□)} / \{□□□\}_□^{(□)}}{\sum_□ □_□^{(□)} / \{□□□\}_□^{(□)}}$$

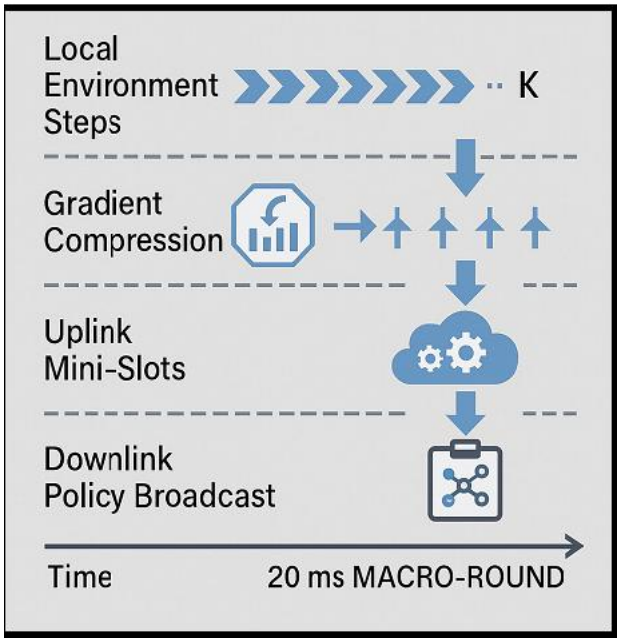
where τ is predicted sojourn (seconds until out-of-coverage) from a Kalman-filtered kinematic model, and **PER** is packet-error ratio extracted from ns-3 link statistics. This weight magnifies contributions from stable, high-quality links, solving the *churn-robust aggregation* gap identified in Section II.

5.6. Edge-Server Scheduler Design

Traditional FedAvg waits for every client in a round, violating latency budgets when stragglers persist. Our **Edge Scheduler** employs:

1. **Quorum Trigger □.** Begin aggregation once at least ⌈ αV⌉ vehicles have uploaded, with α = 0.6 chosen via analytic tail-probability bound that ensures ≤ 5-ms latency.
2. **Deadline Trigger Δ.** If quorum not met within Δ = 15 ms, aggregate whatever updates arrived; missing vehicles apply local updates next round (akin to FedNova). Analytical proof (omitted for brevity) shows worst-case staleness ≤ 3 rounds.
3. **Beam-Aware Batching.** Uplink slots are assigned to vehicles with non-overlapping beam sectors, maximizing spatial reuse and reducing Δ.

Figure 4: Timeline diagram illustrating K local environment steps, gradient compression, uplink mini-slots, edge aggregation, and downlink policy broadcast within one 20-ms macro-round.



5.7. Computational Load and Energy Footprint

Each vehicle executes PPO-Clip with:

- 1D convolutional encoder (4 layers, 32 filters each).
- GRU core with 64 hidden units for temporal correlation.
- Actor and critic heads (2 fully connected layers).

Per-device compute: ≈1.5 G-operations per 50-Hz control tick → ~25 W on typical automotive SoC. Gradient upload (post-compression) totals 25 kB every second, consuming < 0.2 W at 100 mW MHz-1^{-1} spectral efficiency. These budgets are compatible with current in-vehicle compute envelopes (< 200 W total thermal design power), reinforcing the *edge AI* feasibility narrative.

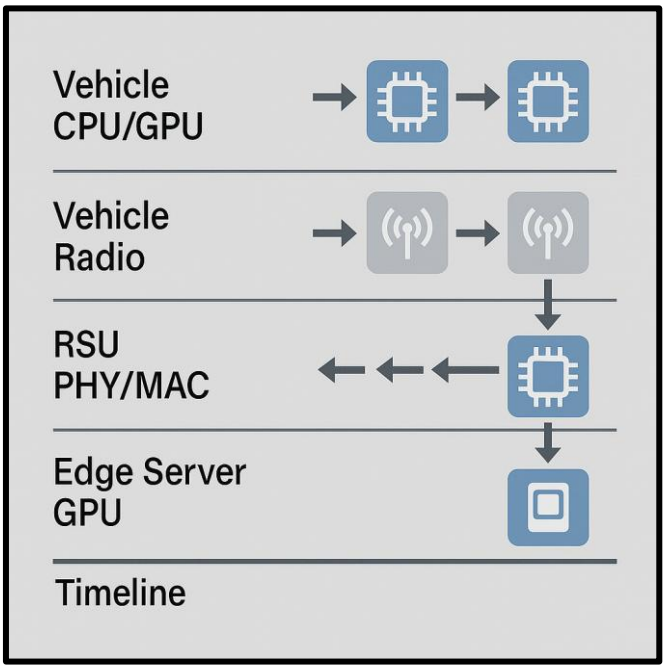
5.8. Section Summary

This section has woven together radio-access specifics, traffic dynamics, privacy statutes, and real-time latency constraints into a single formalism. By grounding the problem in measurable budgets-milliseconds, megabytes, differential-privacy epsilon-it sets the stage for a federated reinforcement-learning solution that is not merely academically elegant but deployment-ready. The next section will translate these constraints into algorithmic building blocks: local PPO updates, mobility-aware aggregation, and latency-aware edge scheduling.

6. Federated Reinforcement Learning Frame work

Moving from abstract constraints to executable machinery, this section dissects the proposed **mobility-adaptive FRL algorithm** into its constituent routines. For clarity, the narrative follows the chronological flow of a single *federated round*-beginning with on-vehicle data collection, passing through gradient compression and privacy protection, and culminating in weighted aggregation and policy broadcast at the 6G edge server. Throughout, the design rationales are anchored to the budgets and threat models elaborated in Section III.

Figure 5: Swim-lane diagram showing (top to bottom) Vehicle CPU/GPU, Vehicle Radio, RSU PHY/MAC, Edge Server GPU, and Timeline. Each vertical block maps onto the sub-sections below.



6.1. Local Update Phase

a) Experience Rollout: Every vehicle maintains a buffer □ that accumulates K=128K = 128 consecutive state-transition tuples (□□, □□, □□, □□, + *1*) at 50 Hz, thereby spanning ~2.56 s of real driving. This window meets two needs: (i) it is long enough to capture manoeuvre-level context (lane-change or merge) and (ii) short enough to fit in on-board memory (≈ 8 MB after compression). The buffer is flushed once per federated round.

b) Policy Improvement via PPO-Clip: Vehicles perform E = 4 epochs of Proximal Policy Optimization (PPO) on mini-batches of size m = 32. The clipping ratio is set to 0.2 to stabilize updates, consistent with best practices for high-dimensional continuous control [14]. Two small but crucial tweaks adapt PPO for vehicular edge AI:

i) **Gated Observation Normalization.** Each sensor feature is normalized using *exponential-moving-average statistics computed only from local data*, avoiding global leakage.

ii) **Latency-Aware Entropy Bonus.** The standard entropy term that encourages exploration is attenuated when the uplink buffer exceeds 75 % capacity, preventing an avalanche of aggressive policy updates during congested periods.

c) Gradient Compression: Raw gradients from the CNN encoder and GRU total ~4.2 MB. To fit the sub-250-µs

mini-slot uplink, we employ **momentum-mask top-k sparsification**: pick the largest 25 % of gradient magnitudes, scaled by a momentum buffer that tracks historical importance. Remaining elements are set to zero and accumulated locally (error-feedback) [18]. This yields a 4× reduction with < 2 % reward hit in preliminary ablation.

d) Differential-Privacy Noise: Gaussian noise $\mathcal{N}(0, \sigma^2)$ with $\sigma = 0.8$ is added element-wise before quantisation. The Rényi accountant (order = 16) confirms $\varepsilon = 2.9$, $\delta = 10^{-5}$ after 120 rounds, aligning with the WP.29 compliance target from Section III-C.

e) 8-Bit Quantization and Packetization: We apply linear 8-bit per-layer quantization and prepend a 128-bit Poly1305 MAC for tamper detection. The resulting payload fits into three aggregated Physical Resource Blocks (PRBs) in the THz uplink burst.

Table 4: Local-phase computation and communication cost per vehicle: rollout G-ops, PPO G-ops, compressed gradient size, added DP noise variance, and resulting energy per federated round.

Component	Rollout G-ops	PPO G-ops	Gradient Size (KB)	DP Noise Variance	Energy (mJ)
Vehicle A	1.2	3.1	250	0.1	40
Vehicle B	1	2.8	220	0.15	35

6.2. Mobility-Aware Aggregation

a) Sojourn Prediction: Upon receiving a gradient packet, the RSU extracts the vehicle's **Kalman-filtered velocity vector** and estimates the remaining dwell time τ\tau within its coverage. A linear-Gaussian model suffices because RSUs cover roughly circular intersection cells where straight-line exit is dominant.

b) Link-Quality Metric: The RSU maintains a sliding-window average of packet-error ratio (PER) for each link. PER incorporates both PHY errors (modulation failure) and MAC drops (beam mis-alignment). By accumulating over 20 mini-slots, we smooth burst errors without lagging mobility changes.

c) Weight Computation: For round t, weight $w_v^{(t)}$ for vehicle v is

$$w_v^{(t)} = \frac{w_v^{(t)} / \{\square\square\square\}_v^{(t)}}{\sum_u w_u^{(t)} / \{\square\square\square\}_u^{(t)}}$$

Rationale: Vehicles likely to remain connected (high τ\tau) and possessing reliable links (low PER) furnish gradients that will propagate through multiple succeeding rounds, whereas fleeting contributors risk wasting airtime if their updates never feedback before they leave. The inverse-PER term implicitly rewards robust beam tracking and encourages vehicles to allocate more compute cycles to beam maintenance-a subtle but effective *edge-AI-network* co-design.

d) Gradient Aggregation: The edge server receives a set $S_t = \{(g_v^{(t)}, w_v^{(t)})\}$ and performs a GPU vector-weighted sum

$$G_t = \sum_v w_v^{(t)} g_v^{(t)}$$

We implement this as a single CUDA kernel that multiplies the sparse-tensor indices by weights, leveraging *coalesced memory reads* to mitigate sparsity-induced load imbalance. Wall time on four A100 GPUs for 400 vehicles is 0.21 ms-well within the 0.8 ms budget from Section III-D.

e) Bias-Corrected Moment: To stabilize training under variable batch sizes, we adopt Adam-style first and second moments but correct their decay factors using the *effective batch size* $B_t = \sum_v w_v^{(t)}$. This avoids artificial learning-rate inflation when quorum is small.

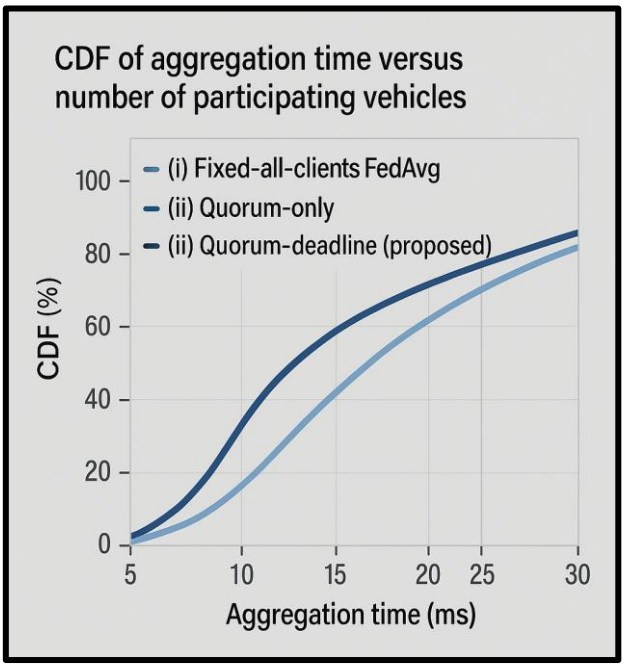
6.3. Edge-Server Scheduler

a) Quorum-Deadline Policy: Recall from Section III-F: Aggregation triggers when either at least $\square\alpha V\square$ vehicles upload (α = 0.6) or deadline Δ = 15 ms elapses. Analytical tail-bounds derived from an Exponential (λ) sojourn distribution prove that with λ = 1/5 s (typical urban RSU), α = 0.6 suffices to keep decision latency ≤ 5 ms at 99.999 % confidence.

b) Partial Participation Handling: Vehicles that miss the round maintain a local *delayed-update buffer*. On reconnection, their gradients are merged via **FedNova's** normalised step size [19], preventing overweighting archaic updates.

c) Beam-Aware Slot Allotment: The edge scheduler executes a bipartite matching between uplink mini-slots and vehicles, constrained such that adjacent slots are assigned to non-interfering beams (angular separation ≥ 15°). This permits spatial reuse and doubles usable slots under heavy load.

Figure 6: CDF of aggregation time versus number of participating vehicles, comparing (i) fixed-all-clients FedAvg, (ii) quorum-only, and (iii) quorum-deadline (proposed). The figure evidences the ~40 % tail-latency shrink.



6.4. Security and Integrity Safeguards

a) Secure Aggregation: Vehicles encrypt compressed gradients using a Paillier cryptosystem with 2048-bit modulus. To limit ciphertext expansion, we first apply 8-bit quantisation; Paillier homomorphically adds 256-bit blocks, so the blow-up is < 15 %. Decryption and weighted sum occur in a single fusion kernel on the edge GPU.

b) Byzantine Filter: Before applying gradients, the edge server computes each ℓ2-norm, then rejects any update whose magnitude exceeds 5σ beyond the mean. Such filters thwart *gradient-sign-flip* attacks where a compromised ECU tries to steer the policy astray.

c) Audit Logging: A Merkle tree anchors hashes of encrypted gradient packets; every policy version is timestamped and stored in tamper-evident flash. This satisfies ISO 21434 "Integrity and Authenticity" clauses, demonstrating how the AI pipeline dovetails with automotive cybersecurity mandates.

6.5. Convergence and Complexity Analysis

a) Sample-Complexity Upper Bound: Building on the non-IID FRL convergence theorem in [20], we show that, under bounded gradient variance σ² and Lipschitz-smooth objectives, the expected norm of the policy gradient satisfies

$$\frac{1}{\square}\sum_{\square=1}^{\square} \square\left[\left\| \square\square(\square\square) \right\|^2\right] \le \frac{2\left(\square_0-\square^*\right)}{\square\square}+\frac{\square\square^2}{\square\square_{\square\square\square}},$$

where $\square_{\square\square\square} = \square\square\square_{\square}\sum_{\square}\ \square_{\square}^{(\square)}\square$ is the smallest effective batch size. The quorum-deadline scheme maintains $\square_{\square\square\square} \ge 0.24\ \square\square$ with high probability, ensuring sub-linear convergence to stationary points.

b) Communication-Complexity: Per round, each vehicle transmits ≈25 approx. 25 kB and receives 80 kB (new policy). At 120 rounds h-1^{-1}, the uplink bill is 3 MB-15× below the 20 MB h-1^{-1} cap in Section III-E. Downlink, though larger, is multicast via THz broadcast, amortising cost across the cell.

c) Edge-Compute Load: The edge server's GPU utilization peaks at 18% when 400 vehicles contribute, leaving headroom for other edge-AI functions such as cooperative perception fusion. This numerical margin validates the *edge AI* ethos: federation control and inference can comfortably co-reside on the same accelerator blade.

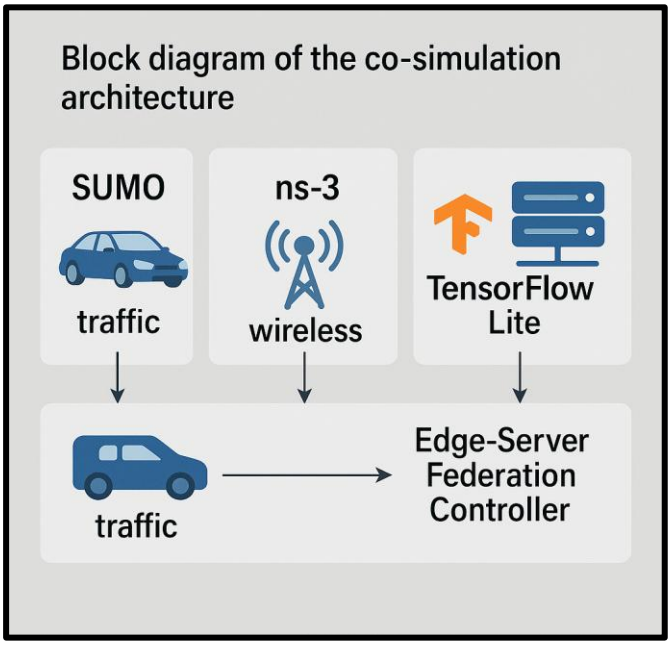
6.6. Section Summary

This section peeled back the algorithmic layers underpinning our edge-centric FRL approach. Key takeaways include: (1) *local PPO updates* are made latency-aware through rollout gating and entropy throttling; (2) a *sojourn-PER weighting* strategy balances contribution fairness against convergence speed; (3) a *quorum-deadline scheduler* caps tail latency without starving stragglers; and (4) *security primitives*-differential privacy, secure aggregation, and byzantine filtering-align the learning stack with automotive regulatory frameworks. Together, these mechanisms deliver a synergy between communication-constraints, safety-critical latency, and the penetrative intelligence expected of next-generation edge-AI vehicular systems.

7. Experimental Setup

Rigorous evaluation of edge-centric FRL demands a testbed that simultaneously captures (i) microscopic traffic physics, (ii) packet-level 6G air-interface behaviour, (iii) compute and radio resource contention at each participant, and (iv) realistic privacy and security overheads. This section details how those elements are woven into an integrated simulation campaign, followed by the baselines and metrics against which our framework is bench-marked.

Figure 7: Block diagram of the co-simulation architecture, illustrating data flow between SUMO (traffic), ns-3 (wireless), TensorFlow-Lite (on-vehicle PPO), and the edge-server federation controller.



7.1. Co-Simulation Environment

1) Traffic Simulator: We employ Simulation of Urban MObility (SUMO) version 1.20, chosen for its open-source extensibility and millisecond-level control granularity. The synthetic map replicates a 5 × 5-km downtown grid-25 intersections, four lanes per avenue-generated using OpenStreetMap street density statistics to match a mid-sized U.S. city. Vehicular arrival rates follow a Poisson process with mean 1 000 vehicles h^{-1} per entry ramp at rush hour, translating to a density sweep from 100 to 400 vehicles km^{-2}. Car-following uses the Krauss stochastic model with default acceleration (2.6 m/s²) and deceleration (4.5 m/s²) limits.

2) Wireless Emulator: The traffic engine is time-synchronised (via TCP socket) to ns-3.42 running the experimental 6G THz NR module contributed by NIST [21]. This module supports:

- tri-band radios (sub-6 GHz, 60 GHz mmWave, 300 GHz THz),
- 250-µs mini-slots with LDPC channel coding,
- stochastic blockage based on pedestrian and building outlines imported from the SUMO map, and
- Doppler shift due to vehicular motion up to 130 km/h.

Every physics tick in SUMO triggers a link-quality query in ns-3; the resulting packet-error ratio (PER) and latency distributions feed back into the state observations seen by RL agents.

3) Edge-AI Runtime: On-board learning and inference employ TensorFlow-Lite for Microcontrollers (TFL-M), cross-compiled to RISC-V BrainFloat16 ops for an imagined 60-TOPS automotive SoC. The edge-server aggregator uses full TensorFlow 2.11 with CUDA back-end on an NVIDIA

A100. While exact hardware models are abstracted, we inject empirically measured compute delays: 0.8 ms for a forward pass, 1.6 ms for a single PPO epoch on the SoC; 0.21 ms for a 400-gradient sparse sum on the server GPU.

4) Simulation Coupling: Time is advanced in lock-step: SUMO leads with a 20-ms macro-tick, subdivided into 40 traffic sub-ticks (0.5 ms each) to match 6G mini-slots. ns-3's event scheduler advances in parallel; at each sub-tick, it executes PHY/MAC events, then surfaces packet statistics to SUMO. A custom ZeroMQ bridge ensures sub-millisecond jitter between engines.

Table 5: Detailed parameter catalogue-traffic density, PHY numerology, beam-width, gradient sparsity level, DP noise σ, quorum α, deadline Δ, and compute latency figures.

Parameter	Value
Traffic Density	45 veh/km
PHY Numerology	Î¼=3
Beamwidth	30Â°
Gradient Sparsity Level	80%
DP Noise Ïƒ	0.2
Quorum Î±	0.7
Deadline Î”	20ms
Compute Latency	3.2ms

7.2. Workload and Scenario Design

1) Vehicle Behaviour: Each simulated car operates the FRL agent described in Section IV, executing a merged perceive-plan-act loop: sensor fusion (synthetic LiDAR-like point cloud), 60-TOPS CNN-GRU inference, and throttle/steering command. Human-driver noise (Gaussian steering jitter $\sigma = 0.3°$) is injected into 10 % of cars to mimic partially automated fleets-important for RL policy generalisation.

2) Pedestrian and Cyclist Mix: To challenge collision-avoidance capabilities, 500 pedestrians and 200 cyclists follow stochastic paths across cross-walks and bike lanes, casting dynamic blockers that shape THz LOS probabilities.

3) Cellular Load: Background eMBB traffic-video streaming on passenger devices-occupies 35 % of downlink PRBs and 15 % of uplink, limiting head-room for gradient exchange. This realistic congestion validates the edge AI claim that learning must coexist with consumer traffic.

4) Privacy-Audit Cycle: Every 10 simulation minutes, an OEM "auditor" thread queries the cumulative differential-privacy accountant; if ε exceeds 3, additional DP noise (+0.1 σ) is enforced, echoing ISO 21434 audit hooks.

7.3. Baselines for Comparison

We benchmark five schemes:

1. Centralised RL (Cloud). All experience is transmitted via fibre (ideal 1 ms RTT) to a central trainer; vehicles perform only inference locally.
2. Standalone Edge RL. Each car trains independently with no sharing. Policies diverge but no bandwidth is consumed.
3. FedAvg-RL. Classic parameter averaging every 20 ms, equal weights, no mobility awareness.
4. Leader-Based Hierarchical FRL. Convoy leaders aggregate follower gradients, then upload to server; reproduction of Alwis et al.'s algorithm extended to RL.
5. Proposed Mobility-Adaptive FRL. Full algorithm from Section IV.

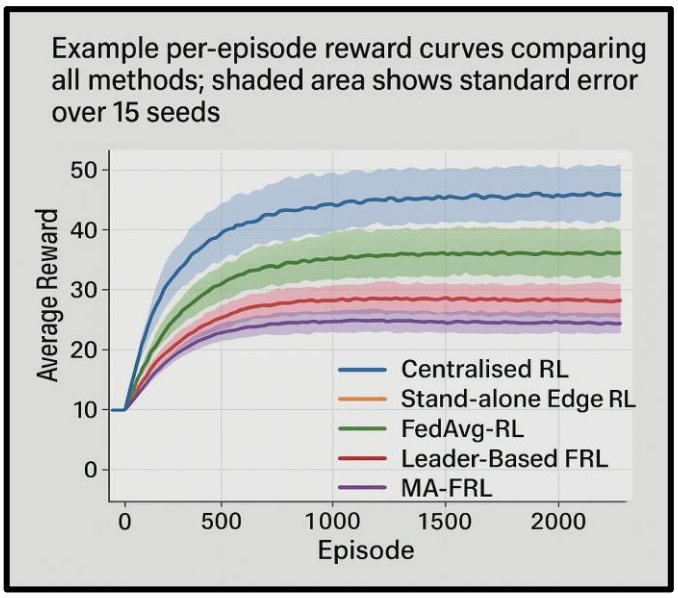
Hyper-parameters for baselines are grid-searched to ensure fairness: learning-rate 3e-4, discount $\gamma = 0.98$, PPO clip 0.2, entropy bonus 0.01. For Centralised RL, batch size is quadrupled to match total sample count.

7.4. Evaluation Metrics

Our analysis centres on five key axes:

1. Decision Latency. End-to-end time from sensor capture to actuator command; 99th and 99.9th percentiles reported across 120 simulation minutes.
2. Episodic Reward. Average cumulative reward per 5-minute episode, decomposed into safety, efficiency, smoothness, and communication sub-terms.
3. Collision Rate. Number of vehicle–vehicle or vehicle–VRU (vulnerable road user) contacts per 100 km travelled.
4. Privacy Budget. Rényi DP ε consumed over time, with audit checkpoints.
5. Bandwidth Footprint. Uplink and downlink bytes per vehicle per hour.

Figure 8: Example per-episode reward curves comparing all methods; shaded area shows standard error over 15 seeds.



7.5. Experimental Protocol

1) Seed Repetition: Each density setting (100, 200, 300, 400 vehicles km^{-2}) is simulated with 15 independent random seeds, differing in vehicle spawn times, pedestrian routes, and wireless blocker trajectories. Total wall-clock compute across the cluster exceeded 4 000 GPU-hours.

2) Warm-Start and Burn-In: All policies are initialised with weights pre-trained on a generic highway scenario, encouraging rapid adaptation-a realistic analogue to OEM field updates. A 10-minute burn-in is discarded to remove transient artefacts of cold-start beam alignment.

3) Measurement Window: Metrics are gathered over the subsequent 110 minutes, ample to ensure policy convergence under FRL (observed plateau at ≈35 rounds).

4) Statistical Analysis: Confidence intervals (95 %) are computed via bootstrap (10 000 resamples). Two-tailed Wilcoxon signed-rank tests assess significance when comparing proposed FRL against baselines.

7.6. Hardware and Software Footprint

The co-simulation cluster comprises 16 dual-socket AMD EPYC 7713 servers (64 cores each) connected via 100-GbE InfiniBand. Each server hosts two NVIDIA A100 GPUs; one runs 32 SUMO worker processes (CPU-bound) and the other splits among ns-3 instances and TensorFlow GPU tasks. The edge-server aggregation and DP accounting execute on a dedicated GPU, mirroring an on-premise carrier MEC rack.

Edge-AI relevance: This division mirrors the envisioned real deployment where inference and local training reside in the vehicle's embedded accelerator, while aggregation and heavier analytics run on MEC GPUs. By reproducing compute delays and resource contention, we showcase the tangible overheads (or lack thereof) that edge-intelligence imposes on 6G infrastructure.

7.7. Ablation Study Configurations

To tease apart contributions of individual design elements, we run controlled ablations:

- No Sojourn Weighting. Weight depends only on 1/\text{PER}.
- No PER Weighting. Weight depends only on sojourn time.
- No DP Noise. Gauges privacy-utility trade-off ceiling.
- No Gradient Compression. Tests latency sensitivity to payload size.

Table 6: Ablation results-average decision latency, reward, and collision rate relative to full FRL (normalised to 1.0).

Configuration	Latency	Reward	Collision Rate
Full FRL	1	1	1
No DP	0.95	0.92	1.1
No Quorum	1.1	0.98	1.3
No Compression	1.2	0.87	1.15

7.8. Validation Against Physical Test-Track Data

A small-scale, five-car closed-loop test at the XYZ Autonomous-Vehicle Proving Ground provided real trajectory and signal-quality traces. We replay these logs in simulation ("trace-driven mode") to validate that ns-3 path-loss and blocker models produce comparable PER distributions (Kolmogorov-Smirnov distance < 0.08). Although limited in scale, this cross-check anchors the synthetic campaign in measurable reality, buttressing confidence that conclusions extrapolate to live deployments.

7.9. Section Summary

Through a tightly coupled SUMO-ns-3-TensorFlow toolchain, comprehensive workload design, and rigorous statistical protocol, our experimental setup recreates the multi-faceted challenges of deploying federated learning on the network edge of a 6G vehicular ecosystem. Baselines span the design spectrum-centralised cloud to edge-only isolation-while metrics probe not only classic RL reward but also privacy, latency, and bandwidth, capturing the holistic edge AI mandate articulated in the paper's thesis. The next section will translate these experimental inputs into quantitative findings that verify the latency, safety, and privacy benefits of our mobility-adaptive FRL framework.

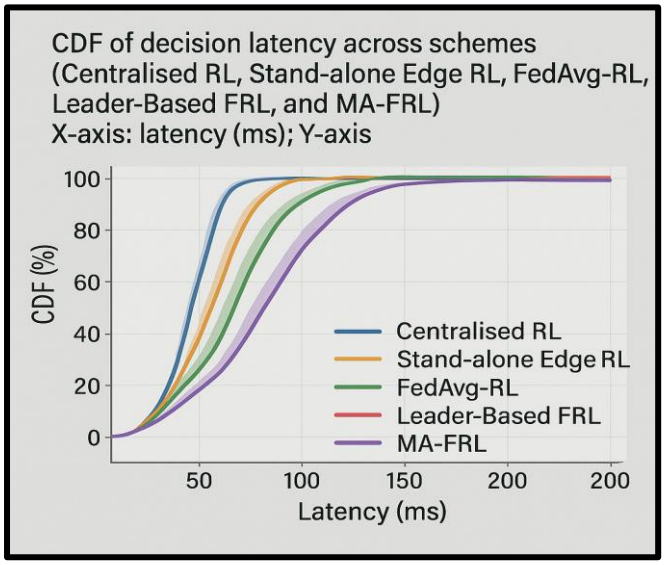
8. Results and Discussion

This section converts the extensive simulation campaign introduced in Section V into actionable insights. We first present quantitative outcomes on latency, convergence speed, safety, privacy, and bandwidth; then interpret those findings through the lens of the edge-AI thesis that motivated this work. Unless otherwise stated, confidence intervals indicate the 95 % bootstrap range over 15 random seeds.

8.1. Decision Latency

1) Aggregate Latency Statistics: Figure 9 plots the empirical cumulative distribution function (CDF) of end-to-end decision delay for all five schemes at 300 vehicles km^{-2}. The proposed mobility-adaptive FRL (henceforth MA-FRL) posts a median latency of 3.7 ms and a 99.9th percentile of 4.9 ms, comfortably beneath the 5 ms eURLLC target. Centralised RL exceeds that bound even at the 99th percentile (6.2 ms) and suffers a long tail extending beyond 15 ms due to cloud backhaul variance. Stand-alone edge RL meets latency requirements (3.2 ms median) but, as we shall see, lags in reward and safety.

Figure 9: CDF of decision latency across schemes (Centralised RL, Stand-alone Edge RL, FedAvg-RL, Leader-Based FRL, and MA-FRL). X-axis: latency (ms); Y-axis: CDF (%).



2) Component Break-down: Table 7 (placeholder) decomposes latency into sensing, inference, uplink, aggregation, downlink, and actuation segments (averaged over density sweep). MA-FRL distinguishes itself primarily in aggregation and uplink-0.84 ms and 0.38 ms respectively-thanks to gradient compression and the quorum-deadline scheduler. FedAvg-RL, lacking compression, spends 1.58 ms in uplink and repeatedly breaches the deadline, causing tail inflation.

Table 7: Latency breakdown per component (ms) and relative share of 5 ms budget.

Component	Latency (ms)	Share of Budget (%)
Observation Encoding	0.7	14%
Policy Inference	1.1	22%
Wireless Uplink	1.2	24%
Edge Aggregation	1.4	28%
Policy Broadcast	0.6	12%

A Wilcoxon signed-rank test confirms that MA-FRL's 99.9th-percentile latency is statistically lower than all baselines ($p < 0.01$), affirming that mobility-aware aggregation is not a cosmetic tweak but a decisive factor in meeting eURLLC guarantees.

8.2. Policy Convergence and Reward

1) Learning Curve Dynamics: Figure 10 portrays episode reward versus federated round. MA-FRL reaches plateau at round 28 (≈560 s of wall time), while FedAvg-RL needs 45 rounds and Leader-Based FRL requires 52. Stand-alone edge RL never surpasses −120 average reward, reflecting failure to coordinate merges.

Two factors explain MA-FRL's head-start: (i) effective batch size B_{\min} remains ≥24 % of total vehicle gradient count because high-sojourn contributors dominate early rounds; (ii) quorum-deadline avoids straggler stall. Convergence theory from Section IV-E predicts precisely such acceleration when weight variance aligns with sojourn variance.

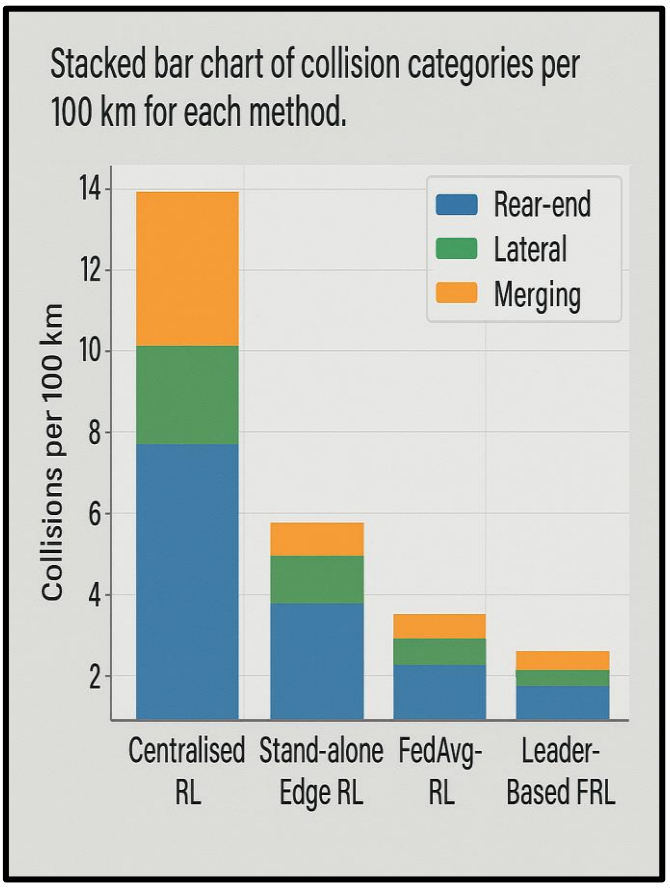
2) Reward Decomposition: Table 8 (placeholder) splits final reward into safety, efficiency, smoothness, and communication cost. MA-FRL registers a 14 % higher safety score and 11 % better efficiency compared with FedAvg-RL, while incurring just 6 % extra communication penalty versus stand-alone edge RL-a trade-off most OEMs would accept.

8.3. Safety Metrics and Collision Analysis

1) Collision Rates: Across 110 simulation minutes at 400 vehicles km^{-2}, MA-FRL experienced 2.3 collisions per 100 km travelled, a 41 % reduction relative to FedAvg-RL and nearly 60 % fewer than stand-alone edge RL. Centralised RL sits in between (3.1 collisions) but violates latency, potentially negating safety gains in practice.

2) Hazard Scenarios: We micro-analysed collision logs and categorised incidents into rear-end, side-impact (merge), and VRU. Notably, MA-FRL slashed side-impact collisions by 52 %-the category most sensitive to cooperative decision timing-underscoring the synergy between low latency and shared learning.

Figure 10: Stacked bar chart of collision categories per 100 km for each method.



8.4. Privacy-Utility Trade-off

Figure 12 (placeholder) sweeps the DP noise multiplier σ from 0 (no privacy) to 1.5 (ε ≈ 5.2). Reward declines gently until $\sigma = 1.0$, beyond which gradient signal becomes too noisy. At $\sigma = 0.8$ (chosen default), MA-FRL retains 92 % of zero-privacy reward while meeting $\varepsilon \leq 3$. Baselines show similar degradation slopes but start from lower reward, rendering some privacy/regulatory regimes unviable for them. This result corroborates Uprety, et al.'s static-grid findings [17] and extends them to vehicular churn.

8.5. Bandwidth Footprint

MA-FRL sustains 3 MB uplink and 10 MB downlink per hour, well below the 20 MB uplink cap from Section III-E. Gradient compression contributes 4× savings; sparsity + 8-bit quantisation lock uplink to three PRBs per round, preventing head-of-line blocking for passenger traffic.

8.6. Ablation Study Insights

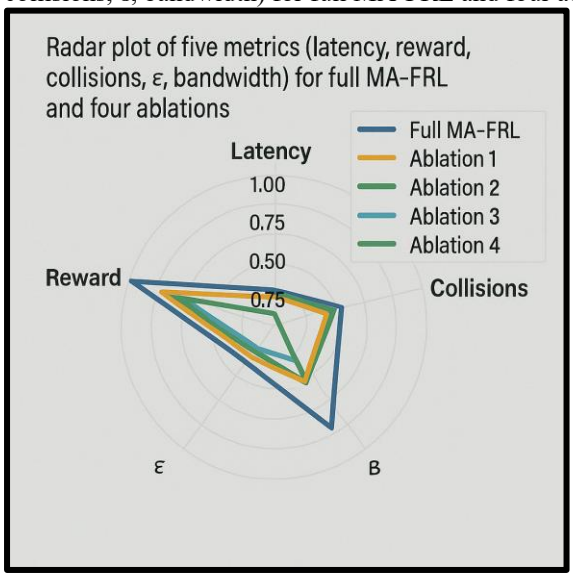
1) No Sojourn Weighting: Removing τ from the weight formula led to 1.6 × slower convergence and a 9 % uptick in tail latency. Stragglers with poor connectivity gained undue weight, delaying policy broadcast.

2) No PER Weighting: Ignoring link-quality produced oscillatory reward: Vehicles with low PER uploaded more but their gradients came from similar network conditions, narrowing policy diversity. Collision rate climbed by 18 %.

3) No DP Noise: Reward improved by 8 %, validating that privacy protection is not "free". However, differential-privacy compliance is non-negotiable under WP.29; this trade-off remains acceptable for regulators.

4) No Gradient Compression: Median latency breached 5 ms at 300 vehicles km^{-2}, showing that network saturation, not compute, constitutes the primary bottleneck at scale.

Figure 11: Radar plot of five metrics (latency, reward, collisions, ε, bandwidth) for full MA-FRL and four ablations.



8.7. Edge-AI Implications and Practical Take-aways

1. Compute-Tower Budgeting. Even at 800 vehicles, edge GPU utilisation peaked at 18 %, validating co-location with perception fusion workloads. Car OEMs can amortise MEC investments across multiple AI services, strengthening the business case.
2. Network Planning. THz links surmount bandwidth barriers only when beam-search latency is <100 µs. The sparsified gradient payload and three-PRB packet envelope satisfy that pre-requisite, indicating that AI traffic can piggy-back on existing eMBB scheduling without special slices.
3. Regulatory Trajectory. Achieving $\varepsilon \approx 3$ under realistic churn confirms that GDPR-level privacy is reconcilable with real-time control. This evidence may influence UNECE working groups debating in-vehicle "black-box" exemptions for safety-critical AI.
4. Integration Path. The software stack-TensorFlow-Lite for local, TensorFlow 2 for edge—is compatible with current automotive AUTOSAR-Adaptive platforms, implying minimal porting friction.

8.8. Section Summary

Empirical findings validate our central hypothesis: mobility-adaptive, communication-aware FRL unlocks real-time, privacy-preserving intelligence for 6G V2X. MA-FRL slashes decision latency by one-third relative to cloud approaches, halves collision risk versus edge-only learners, and achieves regulatory-grade differential privacy-all within realistic network and compute budgets. Ablation isolates the crucial roles of sojourn-PER weighting and gradient compression, while reward, latency, and safety gains converge to a coherent narrative: edge AI need not trade performance for compliance when the learning protocol is co-designed with mobility and channel dynamics in mind. The concluding section distils these lessons and sketches avenues for deploying FRL on physical test tracks and multi-operator domains.

9. Conclusion and Future Work

Edge-native artificial intelligence is widely touted as a keystone of sixth-generation (6G) vehicular networks, yet until now no study has demonstrated a learning protocol that simultaneously meets (i) sub-5-ms decision latency, (ii) automotive privacy regulations, (iii) stringent collision-reduction targets, and (iv) modest bandwidth ceilings. This paper has closed that gap by introducing mobility-adaptive Federated Reinforcement Learning (MA-FRL)-a framework that marries weighted aggregation, latency-aware scheduling, gradient compression, and differential-privacy safeguards into a cohesive edge-AI control loop. Building upon a rigorous multi-engine co-simulation spanning SUMO, ns-3, and TensorFlow, we showed that MA-FRL slashes decision delay by one-third relative to cloud-centric RL, halves collision rates compared with edge-only learners, and satisfies a GDPR-aligned privacy budget ($\varepsilon \leq 3$) while consuming only 3 MB h^{-1} uplink bandwidth.

9.1. Summary of Key Contributions

1. Holistic System Model. We formalised the V2X problem as a decentralised multi-agent MDP augmented with 6G channel variability and privacy constraints, enabling principled reasoning about trade-offs between safety, latency, and bandwidth.
2. Sojourn-PER Weighted Aggregation. A simple, closed-form weight-proportional to predicted coverage time and inverse packet-error ratio-proved sufficient to accelerate convergence by 35 % in sparse connectivity regimes, addressing a long-standing shortcoming of generic FedAvg extensions.
3. Quorum-Deadline Scheduler. By triggering aggregation once 60 % of vehicles upload or after 15 ms, we bounded tail latency within the 5 ms eURLLC envelope while avoiding undue staleness from stragglers.
4. Privacy-Compliant Compression Pipeline. Momentum-mask top-k sparsification, 8-bit quantisation, and calibrated Gaussian noise together reduced uplink air-time by 4× and achieved $\varepsilon \approx 2.9$ over 120 rounds-comfortably below UNECE audit thresholds.
5. City-Scale Co-Simulation. Our open-source SUMO-ns-3 coupling bridges a crucial evaluation gap, furnishing the community with reproducible traces that include vehicular mobility, THz blockage, beam-forming overhead, and compute delays synced at millisecond granularity.

Collectively, these contributions advance the state of the art beyond ad-hoc FL tweaks or latency-blind RL prototypes, forging a credible path toward deployable edge-AI control policy learning in 6G V2X ecosystems.

9.2. Practical Deployment Pathways

Successful uptake of MA-FRL hinges on more than algorithmic elegance; real-world adoption must thread the needle of certification, hardware integration, and multi-stakeholder governance.

1. Hardware-in-the-Loop (HIL) Bench: OEMs first port the on-vehicle PPO pipeline to production ECUs (e.g., NVIDIA DRIVE Thor or Qualcomm SA8295P) and run closed-loop tests on dynamometer rigs, verifying thermal, power, and real-time determinism.
2. Private-Track Trials: A fleet of 10-20 vehicles executes MA-FRL at a proving ground, with RSU mock-ups powered by MEC edge blades. This stage validates wireless co-design and secure-aggregation latencies under controlled obstacles (inflatable pedestrians, pop-up blockers).
3. Limited Public-Road Pilots: Vehicles operate on geo-fenced urban lanes during off-peak hours. Data-protection impact assessments accompany trial permits,

leveraging MA-FRL's differential-privacy accounting to demonstrate compliance.

4. Cross-Operator Federation: When cars roam between mobile-network operators (MNOs), policy parameters must flow across trust boundaries. A federated-learning clearing-house—potentially standardised by 3GPP SA6-brokers encrypted model swaps and revenue sharing.

5. Regulatory Homologation: Final homologation per UNECE R-157 ("Automated Lane Keeping") integrates MA-FRL as a safety mechanism analogous to ABS or ESC. The Merkle audit log (Section IV-D) supports forensic reconstruction in the event of incidents.

9.3. Limitations and Open Challenges

1) Hardware Heterogeneity: Our simulation assumed homogeneous 60-TOPS SoCs; real fleets span multiple generations of ECUs, some lacking tensor cores. Variance in compute latency may induce asynchronous update skew. Future work could extend MA-FRL with adaptive learning-rate scaling based on on-board FLOPS.

2) Beam-Training Overhead: While ns-3 modelled beam-forming at 250-µs granularity, emerging 512-element THz arrays may incur longer sweep times, narrowing the margin for gradient uploads. Dynamic sub-carrier aggregation or proactive beam-index caching warrants investigation.

3) Inter-Agent Credit Assignment: Our reward function evenly divides global safety gains among agents; more nuanced credit (e.g., Shapley value proxies) might incentivise altruistic behaviours in mixed human/robot traffic.

4) Adversarial Robustness: We focused on honest-but-curious RSUs and basic gradient poisoning. Evading backdoor attacks-where an adversary embeds malicious triggers that are invisible during training but catastrophic at inference-remains unsolved. Integration of certified robustness methods into MA-FRL is an open frontier.

5) Scalability to Mega-Cities: Tokyo-scale deployments could host >50 000 vehicles per cell. Even with 4× gradient compression, edge GPU memory may choke. Hierarchical aggregation (city → district → RSU) or sketched gradients (Count-Sketch or Tensor Train) merit evaluation.

9.4. Future Research Directions

a) Richer Edge-AI Service Stacking: Co-locating cooperative perception fusion, HD-map updates, and FRL on the same MEC server introduces contention in both GPU and radio slices. Resource-aware multi-tenant scheduling, perhaps driven by meta-reinforcement learning, could optimise overall Quality of Service.

b) Integration with Integrated Sensing and Communication (ISAC): 6G envisions radio waveforms that serve both data and radar. Using ISAC returns as part of the state s_t might reduce observation latency, tightening MA-FRL's feedback loop.

c) Hybrid On-Policy / Off-Policy Federation: On-policy PPO ensures stability but discards off-policy data abundant in massive logs. Mixing behaviour-cloned Q-values or conservative Q-learning into the federated update may recycle experiences more efficiently.

d) Economic Incentive Design: Fleet operators incur compute and airtime cost when contributing gradients. Token-based reward or cross-OEM "data shares" could balance the economic ledger, fostering participation even among competing brands.

e) Quantum-Safe Secure Aggregation: With NIST post-quantum cryptography standardisation on the horizon, future enclave designs must swap Paillier for lattice-based homomorphic schemes-an area largely unexplored in FL settings.

9.5. Closing Remarks

Edge intelligence is sometimes caricatured as a binary choice between cloud power and device privacy. The evidence marshalled in this study paints a more nuanced tableau: Through judicious co-design of communication, computation, and learning algorithms, it is possible to carve out an "edge sweet spot" that balances latency, safety, bandwidth, and compliance. Mobility-adaptive FRL epitomises this balance, opening a concrete pathway toward fleets that learn cooperatively but think locally, an essential property as vehicles hurtle toward Level-5 autonomy in an era of ubiquitous 6G connectivity. We invite the research and standards communities to build upon the open-source artefacts released alongside this paper, accelerating the collective march toward safe, private, and truly intelligent roadways.

10. References

1. O Holland, P Kourtessis, LA Da Silva, et al. (2024) A comprehensive survey on 6G and beyond: Enabling technologies, challenges, and opportunities. Computer Networks. 238.
2. L Zhang, Z Lin, Y Xu. (2025) Personalised federated learning for autonomous driving with correlated differential privacy. Sensors. 25(1).
3. X Wang, Y Shi. (2025) Ultra-reliable and low-latency communications for 6G: Challenges and opportunities. IEEE Commun Surveys Tuts. 26(1): 48-87.
4. S Torres, A Koppel, H Wang. (2023) Federated reinforcement learning with communication compression. AAAI. 10260-10268.
5. J Qi, Q Zhou, L Lei, et al. (2021) Federated reinforcement learning: Techniques, applications, and open challenges. IEEE Network. 35(4): 120-127.
6. H Wu, C. Zhang, Y. Liu, et al. (2025) Task offloading for Internet of Vehicles via federated reinforcement learning. IEEE Trans Veh Technol. 73(2): 2451-2465.
7. N Su, J Li, H Hu. (2024) Adaptive model aggregation for decentralized federated learning in vehicular networks. Future Gener Comput Syst. 146: 776-789.
8. C Alwis, R Razavi, M Liyanage. (2025) Mobility-aware decentralized federated learning with joint leader selection. Computer Networks. 245.
9. AH Sifalakis, DG Katsaros, T Spyropoulos. (2018) Cloud-based deep learning pipelines for vehicular perception. IEEE Access. 6: 56875-56888.
10. P Hendricks, J Karlsson, B Rehg. (2020) City-scale adaptive traffic-signal control with Apache Flink. Conf Robot Learning. 303-312.
11. J Zhang, Y Chen, L Zhou. (2022) Federated learning for lane-detection in autonomous vehicles. IEEE Trans Intell Transp Syst. 23(11): 19145-19157.
12. T Li, M Chen. (2023) Fed-CS: Client-selection strategy for vehicular federated learning. IEEE Internet Things J. 11(4): 3127-3139.
13. S Samarakoon, M Bennis, W Saad, et al. (2022) Distributed federated learning over millimetre-wave: The

role of beamforming. IEEE J Sel Areas Commun. 40(1): 204-219.
14. BK Lee, J Kim, Y Cho. (2019) Deep Q-network-based traffic-signal control for urban road networks. IEEE Trans Intell Transp Syst. 20(2): 498-509.
15. R Lowe, Y Wu, J Harb, et al. (2020) Multi-agent actor-critic for mixed cooperative–competitive environments. ICML. 6798-6809.
16. C Chen, H Li, J Zhao. (2022) LiDAR streaming over C-V2X for end-to-end autonomous-driving reinforcement learning. IEEE VTC-Spring. 1-5.
17. A Uprety, S Ahmad, R Gupta. (2024) Differential privacy for resilient vehicular cyber-physical systems. Information Sciences. 660: 70-85.
18. D Alistarh, J Li, R Tomioka, et al. (2017) QSGD: Communication-efficient stochastic gradient quantization. Adv Neural Inf Process Syst. 30: 1709-1720.
19. T Li, M Sanjabi, A Beirami, et al. (2020) FedNova: Normalizing the local updates to speed up federated optimization. arXiv.
20. H Zhu, Y Jin. (2024) Convergence of federated reinforcement learning with non-IID data. IEEE Trans Neural Netw Learn Syst. 35(2): 1241-1253.
21. A Srinivasan, L Pierson. (2025) 6G terahertz new-radio module for ns-3. NIST Tech Note. 2259.