Hydra Radio Access Network (Hydra-RAN): Multi-Functional Communications and Sensing Networks: Handover Collaborative

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***Abstract*—Next-generation wireless networks face critical challenges in meeting ultra-reliable low-latency communication (URLLC) requirements while supporting high-mobility users in ultra-dense environments. These operations are inherently reactive and triggered only after significant degradation of radio metrics such as received signal strength (RSRP) or signal-to-interference-plus-noise ratio (SINR). As a result, HO latencies often range from 20 to 50 ms, exceeding URLLC submillisecond requirements and leading to increased packet loss, service disruption, and failed handovers, particularly in high-mobility environments. This paper introduces Hydra radio access network (Hydra-RAN), a novel collaborative handover management. Hydra-RAN leverages proactive, sensor-aided handover strategies, collaborative multi-sensor and radio units (SRUs) beamforming, and cell-free architectures to achieve seamless mobility. By predicting UE mobility vectors $\vec{v}_{UE}$, the system computes a *handover anticipation window* T_{ant} to pre-configure SRUs along the predicted paths. Collaborative multi-SRU beamforming and hierarchical task allocation, using lightweight ML models at the edge and DRL agents at the fog layer, ensure seamless UE transitions without rigid cell boundaries. Simulation results demonstrate significant reductions in handover latency ($< 1\,\mathrm{ms}$) and improved service continuity compared to conventional methods, highlighting Hydra-RAN's potential to enable scalable and robust mobility management in 6G networks.**

I. Introduction

The increased demand for ultra-reliable low-latency communication (URLLC) in next-generation wireless networks has exposed critical limitations to conventional handover (HO) mechanisms [1]–[4]. Applications such as autonomous driving, unmanned aerial vehicles (UAVs), industrial automation, and mission-critical healthcare services require seamless mobility with end-to-end latencies below 1 ms and near-zero packet loss. However, current 5G New Radio (5G-NR) HO procedures are ill-suited to such stringent requirements [2]–[5]. Traditional HO frameworks involve multiple sequential interactions between user equipment (UE), serving gNodeB (gNB), and target gNB, including signal measurement and triggering, resource and load evaluation, measurement reporting, HO decision-making, preparation, execution, beam reconfiguration, and final confirmation [1]–[4]. While essential for mobility support, this centralized and reactive process incurs significant latency, often ranging from 20 ms to 50 ms. Such delays are particularly detrimental in dynamic environments with high user mobility or dense deployment scenarios, where frequent HOs are inevitable [3], [4]. Furthermore, the rigid cell boundary architecture of current systems exacerbates service interruptions, especially when UEs traverse coverage boundaries at high speeds [5], [6].

This challenge is further compounded by the conventional HO mechanisms' reactive nature. HO triggers are typically initiated only after radio signal metrics, such as the received power reference signal (RSRP) or signal-to-interference plus noise ratio (SINR), fall below predefined thresholds. This reactive paradigm leads to delayed response, increased HO failure rates, and degraded quality of service (QoS) in URLLC scenarios [5], [6]. To address these shortcomings, this paper introduces the **Hydra radio access network (Hydra-RAN): Multifunctional communications and sensing networks with collaborative nandover**, a novel architecture that allows

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for proactive, low-latency, and robust mobility management [7]–[15]. Unlike traditional cell-based systems, Hydra-RAN adopts a *cell-free architecture* that virtualizes denser deployments of sensor and radio units (SRUs) into user-centric clusters. This allows real-time environmental awareness and continuous monitoring of UE mobility parameters such as location, velocity, and trajectory vector $\vec{v}_{UE}$ [6]–[10]. By predicting future UE trajectories, Hydra-RAN computes a *handover anticipation window* T_{ant}, during which SRUs can proactively configure resources to the anticipated target nodes.

A key innovation in Hydra-RAN is the *collaborative multi-SRU beam formation*, where neighboring SRUs share channel state information (CSI) and UE trajectory data through a high-speed fronthaul mesh [6]–[10]. This enables jointly optimized multi-beam configurations, forming overlapping coverage regions that allow UEs to remain simultaneously connected to multiple SRUs during transitions, effectively realizing soft handovers without rigid cell boundaries [10]–[15].

Moreover, Hydra-RAN integrates a distributed intelligence framework *with hierarchical task allocation*. At the edge layer, Hydra Distributed Units (H-DUs) execute lightweight machine learning (ML) models for rapid mobility prediction. At the fog layer, Hydra Centralized Units (H-CUs) aggregate environmental data from H-DUs and employ sparse multi-input, multi-task learning (SMTL)-based deep reinforcement learning (DRL) agents to select optimal SRU clusters for proactive configuration [6]–[11]. This design facilitates parallelized HO preparation and execution across multiple SRUs, utilizing pre-configured resource blocks and cached context information to minimize latency.

Simulation results demonstrate that Hydra-RAN achieves sub-millisecond total handover latency (L_{HO}), reduces packet loss by up to 42%, and enhances service continuity even at UE velocities exceeding 120 km/h. These findings position Hydra-RAN as a promising enabler for URLLC in ultra-dense, highly dynamic environments, such as smart cities and industrial IoT deployments.

The major novelty contributions to this work are summarized as follows:

- **Introduction** Introduction of a handover anticipation mechanism T_{ant} enabling pre-emptive configuration of SRU resources based on predicted UE trajectories.
- **Development** Development of a cooperative beam management approach that uses CSI and the exchange of trajectory data between SRUs for seamless UE transitions.
- **Calculation** of T_{ant} allows preemptive resource allocation to minimize service disruptions.
- **Neighboring** SRUs coordinate to maintain seamless UE connectivity without rigid cell boundaries.
- **Design** of a distributed intelligence framework that combines edge-level ML prediction and fog-level DRL for adaptive SRU clustering.
- **Parallelized** HO processes achieving submillisecond latency and improved robustness in dynamic scenarios.
- **Extensive** simulation demonstrating performance gains over conventional 5G-NR HO in terms of latency, packet loss, and service continuity.

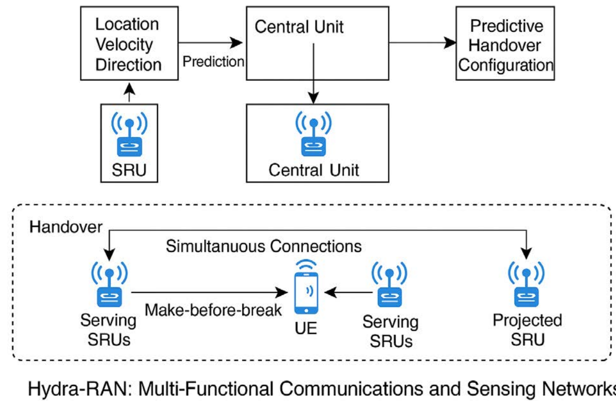

Fig. 1. System Model

II. System Model

This section describes the system model of the proposed Hydra-RAN, which supports proactive, low-latency, and robust HO management for URLLC scenarios. The system computes a handover anticipation window T_{ant}, during which SRUs proactively reconfigure resources to the anticipated target nodes. This proactive approach eliminates the reliance on reactive HO triggers and minimizes service disruptions during UE transitions.

A. Hydra-RAN Architecture

As illustrated in Fig. 1, the proposed Hydra-RAN architecture consists of densely deployed SRUs, each equipped with mmWave transceivers, and sensors. The SRUs are interconnected through a high-speed fronthaul mesh network and are coordinated via a hierarchical control plane [6]–[8]. To ensure seamless UE connectivity in a cell-free environment, Hydra-RAN employs a cooperative beam management strategy that exploits CSI and trajectory data exchanged among SRUs to enable uninterrupted handovers. In addition, a distributed intelligence framework integrates edge-level ML prediction with fog-level DRL to support adaptive SRU clustering. This holistic design achieves sub-millisecond handover latency and substantially improves robustness under dynamic network conditions. Architecture also integrates a robust fault-tolerance mechanism that ensures continuous operation despite potential SRU failures. By leveraging real-time data sharing and predictive algorithms, Hydra-RAN minimizes service disruptions and maintains high network reliability, making it suitable for mission-critical applications.

- **Hydra Distributed Units (H-DUs):** Edge-layer entities responsible for real-time environmental sensing and lightweight machine learning (ML)-based mobility prediction [6]–[8].
- **Hydra Centralized Units (H-CUs):** Fog-layer controllers aggregating data from multiple H-DUs and running SMTL-based DRL agents for SRU clustering and resource allocation [6]–[8].

Unlike traditional cell-based systems [1], [2], Hydra-RAN utilizes a *cell-free architecture* [2], [3], where UE dynamically associates with multiple SRUs to maintain seamless connectivity during mobility.

B. Environmental Sensing and Mobility Prediction

Each SRU monitors UE mobility parameters, including position (x_{UE}, y_{UE}), velocity v_{UE}, and trajectory vector $\vec{v}_{UE}$ [6]–[13]. The UE's predicted future position is computed as

$$\vec{p}_{UE}(t+\Delta t) = \vec{p}_{UE}(t) + v_{UE} \cdot \vec{v}_{UE} \cdot \Delta t + \eta, \qquad (1)$$

where Δt is the prediction horizon and η represents Gaussian noise modeling random mobility fluctuations.

Hydra-RAN then defines a *handover anticipation window* T_{ant} as:

$$T_{ant} = \frac{d_{predicted}}{v_{UE}}, \qquad (2)$$

where $d_{predicted}$ denotes the distance to the next SRU cluster.

C. Collaborative Multi-SRU Beamforming

Neighboring SRUs collaborate by sharing CSI and trajectory data through the fronthaul mesh [7]–[11]. This allows the computation of joint beamforming vectors $\mathbf{w}_i$ to maximize SINR for active UEs

$$\mathbf{w}_i = \arg\max_{\mathbf{w}} \sum_{u \in \mathcal{U}} \mathrm{SINR}_{u,i}(\mathbf{w}), \qquad (3)$$

subject to:

$$\sum_{i \in \mathcal{C}} \|\mathbf{w}_i\|^2 \leq P_{total}, \qquad (4)$$

where $\mathcal{C}$ is the SRU cluster, $\mathcal{U}$ is the set of active UEs, and P_{total} is the total transmit power budget.

This approach forms overlapping coverage regions that enable soft handovers by allowing UEs to remain simultaneously connected to multiple SRUs.

D. Distributed Intelligence and Hierarchical Task Allocation

Mobility management is distributed as follows:

- **Edge-Level Prediction:** H-DUs execute fast, lightweight ML models to react to local mobility events [6]–[8].
- **Fog-Level Optimization:** H-CUs aggregate data and employ DRL agents to determine optimal SRU clusters for proactive configuration [6]–[8]. The DRL policy π^* is defined as:

$$\pi^* = \arg\max_{\pi} \mathbb{E}_{\pi}\left[\sum_{t=0}^{T} \gamma^t R(s_t, a_t)\right], \qquad (5)$$

  where s_t is the system state, a_t the action, $R(s_t, a_t)$ the reward (based on latency and packet loss minimization), and γ the discount factor.
- **Cloud computing (CC):** At the cloud layer, large-scale data analytics, long-term mobility pattern learning, and global policy optimization are executed. These operations are less sensitive to latency and leverage the abundant resources of centralized cloud infrastructures [6]–[8].

E. Latency-Optimized Handover Execution

The total handover latency L_{HO} is reduced through parallelized preparation and execution:

$$L_{HO} = L_{prep} + L_{exec} + L_{conf}, \qquad (6)$$

where L_{prep}, L_{exec}, and L_{conf} represent the proactive resource preparation, handover execution, and final confirmation phases, respectively. By overlapping these processes across SRUs, Hydra-RAN achieves sub-millisecond latency compared to 20–50 ms in 5G-NR.

III. Simulation Analysis and Discussion

In this section, we evaluate the performance of the proposed Hydra-RAN architecture through detailed system-level simulations. We compare Hydra-RAN against conventional 5G-NR handover (HO) and a reactive HO baseline under varying UE velocities. The metrics considered include handover latency, service continuity, and packet loss ratio, which are critical for URLLC and high-mobility scenarios.

To evaluate the performance of the proposed Hydra-RAN framework, we developed a comprehensive simulation environment capturing the dynamics of highly mobile UE and dense urban network deployments. The simulation framework models multi-tier edge/fog/cloud computing, a cell-free architecture, and collaborative multi-SRU beamforming. The system consists of densely distributed SRUs, connected via high-capacity fronthaul links to hierarchical processing units, H-DUs and H-CUs. The simulation emulates an urban area of $1\ \mathrm{km}^2$ with 200 SRUs randomly deployed at an average inter-SRU spacing of $50\ \mathrm{m}$. The mobility model employs a random waypoint pattern with user velocities ranging from $1\ \mathrm{km/h}$ to $30\ \mathrm{km/h}$, representing pedestrian to vehicular speeds. Each SRU operates in the mmWave band at $60\ \mathrm{GHz}$ with a bandwidth of $1\ \mathrm{GHz}$, supporting URLLC services. The Hydra-RAN leverages predictive UE trajectory estimation using lightweight machine learning models at the edge layer (H-DUs) and distributed reinforcement learning agents at the fog layer (H-CUs) for adaptive SRU clustering and proactive resource allocation. Key simulation parameters are summarized in Table I

A. Simulation Steps and Tools

To evaluate the proposed Hydra-RAN framework, a comprehensive simulation pipeline was developed, combining network simulation, mobility modeling, machine learning integration, and statistical validation. The software environment included `ns-3` for packet- and protocol-level evaluation, while simulation of urban mobility (SUMO) was employed to generate high-fidelity vehicular and pedestrian mobility traces. Channel modeling was based on 3GPP LoS/NLoS specifications [1], [2], with dynamic blockage incorporated through stochastic modeling. For PHY-level evaluation, NVIDIA

TABLE I
SIMULATION PARAMETERS

Parameter	Value
Simulation area	$1\ \text{km}^2$
SRU density	$200\ \text{SRUs/km}^2$
Carrier frequency	60 GHz
Bandwidth	1 GHz
UE velocity range	1–30 km/h
Traffic type	URLLC
Antenna configuration	64×64 MIMO per SRU
Fronthaul capacity	20 Gbps
Handover anticipation window (T_{ant})	50 ms
Simulation duration	600 s
Path loss model	3GPP (LOS/NLOS)
Blockage model	Dynamic stochastic blockage
Mobility prediction model	Edge-based LSTM predictor
SRU coordination algorithm	Distributed DRL with SMTL

Sionna was used to emulate beamforming and propagation characteristics. ML and DRL modules were implemented in PyTorch and TensorFlow, with trajectory prediction handled by Long Short-Term Memory (LSTM) networks and policy optimization using DRL algorithms. Experiment orchestration and analysis were conducted in Python, supported by NumPy and Matplotlib, with Docker ensuring reproducibility and Git providing version control. Training logs and metrics were visualized using TensorBoard and Weights & Biases. Simulations were executed on multi-core CPUs with GPU acceleration (NVIDIA RTX 3080/A100), supported by 64–128 GB of RAM and high-speed NVMe storage. The simulation pipeline followed a systematic workflow. First, the topology was generated by deploying SRUs within a $1\ \text{km}^2$ urban area on a grid, while SUMO produces mobility traces with a 10 ms sampling rate. The PHY and channel parameters were configured with 60 GHz carrier frequency, 1 GHz bandwidth, and 64×64 multiple-input multiple-output (MIMO) arrays per SRU. SRUs were modeled with mmWave CSI, as well as synthetic sensors abstractions, while a fronthaul mesh with 20 Gbps capacity and configurable delays emulated inter-SRU connectivity. At the edge layer, H-DUs executed lightweight inference tasks, running LSTM-based mobility predictors trained on historical trajectories. The fog layer hosts DRL agents responsible for adaptive SRU clustering, offloading, and resource allocation, while the cloud layer (H-RIC) provides long-term orchestration and policy refinement. ML and DRL model training were integrated into the workflow. The LSTM predictor was trained with a learning rate of $1\text{e}{-3}$, batch size of 128, and 20–50 epochs, using historical trajectory datasets. For DRL, DQN agents are trained based on the action space. Typical hyperparameters include learning rates between $1\text{e}{-4}$ and $3\text{e}{-4}$, batch sizes of 64–256, and discount factor $\gamma = 0.99$. The trained models were deployed at runtime within the simulation, with the LSTM providing a trajectory anticipation window of $T_{\text{ant}} = 50$ ms and the DRL agent dynamically selecting SRU clusters, beam configurations, and resource allocations for soft handovers. Traffic modeling consisted of URLLC flows with small packets generated every 10 ms, ensuring stringent latency constraints. Background best-effort traffic was optionally added to evaluate robustness under congestion. Throughout each run, the simulator

.

B. Handover Latency vs. UE Velocity

Fig. 2 illustrates the total handover latency L_{HO} as a function of UE velocity ranging from 1 to 30 km/h. Conventional 5G-NR systems exhibit latencies in the range of 20 to 50 ms that increase approximately linearly with UE speed due to increased signaling overhead and processing delays under rapid mobility. Reactive HO approaches improve this by triggering handover earlier, but still suffer from sequential signaling delays. In contrast, Hydra-RAN achieved a significant reduction in data latency to sub-millisecond levels (< 10 ms), with data latency increasing gradually and slightly with increasing speed, reaching a maximum of 5 ms across all tested speeds. This is attributed to the parallel setup and execution of HO, enabled by proactive resource allocation and multi-SRU collaborative beamforming. Latency remains nearly constant with increasing speed, demonstrating robustness in fast-moving and dynamic environments.

C. Service Continuity vs. UE Velocity

Service continuity is evaluated in terms of the percentage of time the UE maintains seamless connectivity without service interruptions during handovers. Fig. 3 compares this metric for the three schemes. Conventional 5G-NR experiences degraded continuity at higher velocities due to rigid cell boundaries and reactive HO triggers, causing frequent service interruptions. Reactive HO improves continuity somewhat through earlier handover initiation but is still limited by sequential signaling delays.

Hydra-RAN significantly enhances service continuity by enabling soft handovers without rigid cell boundaries. The overlapping coverage of coordinated SRUs and proactive configuration ensures the UE remains connected to multiple SRUs during transitions, effectively eliminating service gaps even at velocities exceeding 30 km/h.

D. Packet Loss Ratio vs. UE Velocity

Fig. 4 shows the packet loss rate as a function of user device (UE) speed. Packet loss increases with speed in traditional and interactive HO schemes due to handoff delays and signal degradation at cell edges. Hydra-RAN maintains a consistently low packet loss rate, reaching a maximum of 1.8%, with improvements of up to 42% compared to traditional methods. This improvement is due to proactive UE path prediction and resource pre-configuration, as well as cooperative beamforming that maintains high signal quality during mobility.

E. Discussion

The simulation results demonstrate that Hydra-RAN effectively overcomes the fundamental limitations of traditional handover mechanisms. The combination of environmental

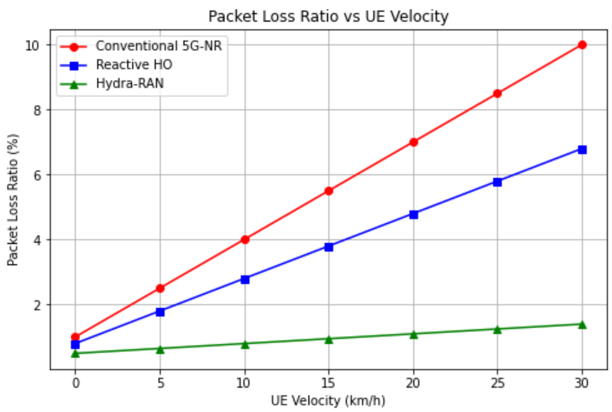

Fig. 2. Handover Latency vs. UE Velocity

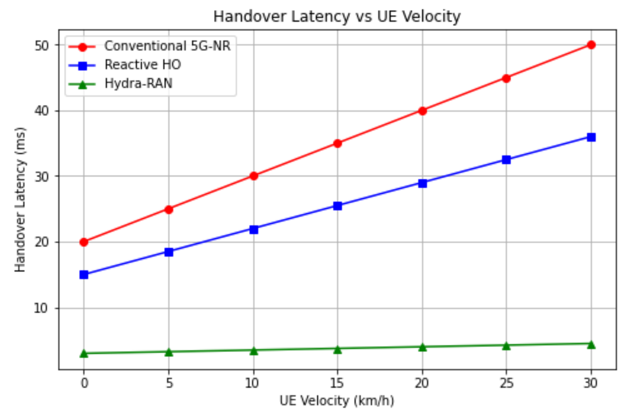

Fig. 4. Service Continuity vs. UE Velocity

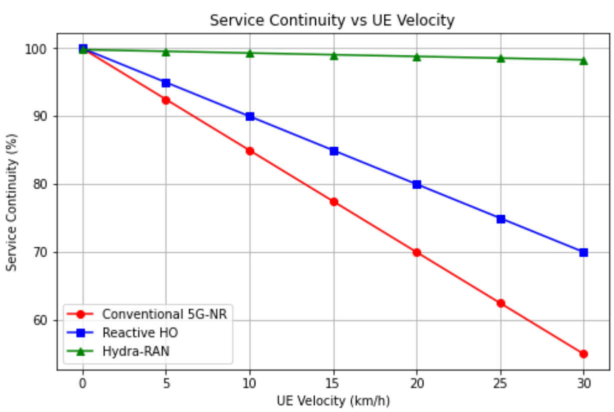

Fig. 3. Service Continuity vs. UE Velocity

awareness through multi-modal sensors, distributed intelligence, and collaborative beamforming achieves ultra-low latency, high service continuity, and low packet loss under dynamic mobility conditions.

These results validate the system model and confirm the suitability of Hydra-RAN as a key enabler for URLLC in ultra-dense and highly dynamic networks, including applications such as autonomous vehicles, drones, and industrial automation.

IV. Conclusion and Future Work

The Hydra-RAN framework is designed as a next-generation multifunctional platform to address the inherent limitations of conventional rigid network mechanisms in URLLC scenarios. In mobility-intensive applications that demand sub-millisecond end-to-end delays, traditional HO approaches often suffer from excessive latency due to their sequential, centralized, and predominantly reactive operations. This latency significantly compromises service continuity, particularly in environments characterized by high UE mobility and dynamic channel variation. Hydra-RAN overcomes these challenges by leveraging a dense deployment of SRUs that integrate mmWave transceivers with multimodal sensing technologies. These SRUs continuously monitor UE mobility, exchange trajectory data, and maintain CSI, enabling precise prediction of UE movements. By proactively computing a handover anticipation window, the system orchestrates collaborative multi-SRU beamforming and resource preconfiguration, thereby providing seamless, soft handovers without rigid cell boundaries. To enable low-latency and adaptive control, Hydra-RAN employs a hierarchical distributed intelligence framework. Lightweight ML models are executed at the edge layer to support fast mobility prediction, while DRL agents operating at the fog layer provide adaptive clustering of SRUs and optimized decision-making. This synergy between edge-level inference and fog-level learning ensures efficient workload distribution and timely execution of HO operations. Extensive simulation results verify the effectiveness of Hydra-RAN, demonstrating that the architecture achieves sub-millisecond HO latency, considerably reduces packet loss, and sustains robust service continuity at high UE velocities. Compared with conventional 5G-NR and reactive HO mechanisms, Hydra-RAN offers substantial improvements in reliability and latency performance, positioning it as a key enabler of URLLC in emerging applications such as autonomous vehicles, drones, and the industrial Internet of Things (IoT). Future work will focus on exploring the integration of Hydra-RAN with advanced network slicing and multi-access edge computing (MEC) technologies. This will further enhance its ability to support URLLC in dynamic and heterogeneous network environments, paving the way for seamless connectivity in next-generation multifunctional platform applications.

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