Hydra Radio Access Network (Hydra-RAN): Multi-Functional Communications and Sensing Networks: A Hierarchical Framework for Task Distribution

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***Abstract*—Next-generation communication networks are increasingly challenged by the stringent requirements of ultra-reliable low-latency communications (URLLC), massive machine-type communications (mMTC), and real-time multi-modal sensing in ultra-dense urban environments. Traditional centralized cloud computing architectures often suffer from excessive latency and bandwidth constraints, making them unsuitable for supporting latency-sensitive and computationally intensive applications. The purpose of this paper is to demonstrate the capabilities of the Hydra Radio Access Network (Hydra-RAN) framework for dynamic, context-aware computational task distribution across hierarchical tiers comprising edge computing (EC), fog computing (FC), and cloud computing (CC). Hydra-RAN integrates densely deployed sensor and radio units (SRUs), leveraging a proactive handover paradigm and multi-SRU collaborative beamforming to enhance mobility management. A key innovation is the context-aware task distributor mechanism, which adaptively allocates workloads based on latency sensitivity, computational intensity, and data locality. The EC layer Hydra distributed units (H-DUs) handle initial sensor data preprocessing and lightweight machine learning (ML) predictions, while the FC layer (Hydra centralized units, H-CUs) aggregates edge results and employs sequential multi-task learning (SMTL)-based deep reinforcement learning (DRL) agents for regional decision-making. The CC layer Hydra RAN intelligent controllers (H-RICs) orchestrate network-wide semantic knowledge refinement and long-term model updates. Extensive simulation results show that Hydra-RAN reduces average response time by up to 45%, achieves balanced workload distribution across all tiers, and improves system scalability under dynamic traffic and mobility conditions. These results demonstrate Hydra-RAN's potential as an enabler for future multifunctional communications and sensing networks, delivering robust, low-latency, and intelligent distributed operations in highly dynamic environments.**

***Index Terms*—Hydra-RAN, edge computing, fog computing, cloud computing, task distribution, multi-functional networks, deep reinforcement learning (DRL), ultra-reliable low-latency communications (URLLC).**

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I. Introduction

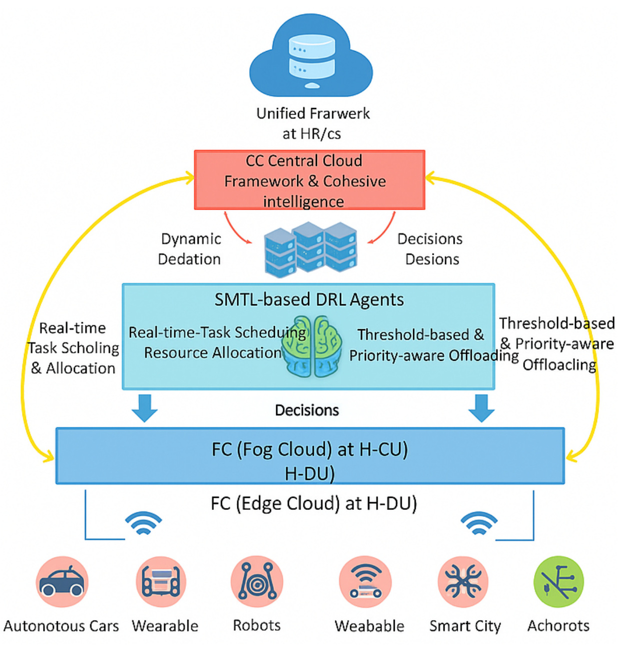

Fig. 1. Hydra Radio Access Network (Hydra-RAN) framework for dynamic, context-aware computational task distribution across hierarchical tiers comprising edge computing (EC), fog computing (FC), and cloud computing (CC).

The rapid proliferation of smart devices, autonomous systems, and Internet of Things (IoT) applications has significantly increased the demand for ultra-reliable low-latency communications (URLLC) and massive machine-type communications (mMTC) in beyond-5G and 6G networks [1]–

[5]. Conventional cloud-centric architectures, while offering substantial computational resources, often suffer from high transmission delays, bandwidth overhead, and backhaul congestion, thereby limiting their suitability for mission-critical and latency-sensitive services [1], [2]. These limitations have accelerated the adoption of distributed paradigms such as edge computing (EC) and fog computing (FC), which enable data processing closer to end devices to reduce latency and alleviate core network traffic [1]–[3].

Despite their advantages, EC and FC deployments in isolation face critical challenges, including resource constraints, scalability limitations, and coordination inefficiencies [1], [3]. Edge nodes, though proximate to users, are typically resource-limited and prone to bottlenecks under dense workloads [1]. Fog nodes, while offering intermediate computational capacity, often experience congestion and lack a global network perspective, reducing their effectiveness in large-scale optimization tasks [2]–[4]. These shortcomings highlight the need for a hierarchical paradigm that synergistically integrates EC, FC, and cloud computing (CC) into a unified architecture to achieve scalability, adaptability, and system-wide optimization.

In this paper, we propose a Hydra-RAN-enabled hierarchical framework for intelligent and dynamic task distribution across EC, FC, and CC layers [5]–[7]. The framework introduces two core innovations. First, Hydra-RAN employs a context-aware task distributor that leverages heterogeneous sensing data (e.g., cameras, mmWave radars) and channel state information (CSI) to enable real-time, adaptive workload allocation [8]–[13]. Second, the fog layer integrates a sparse multi-input, multi-task learning (SMTL)-based deep reinforcement learning (DRL) mechanism to optimize task offloading under dynamic traffic and network conditions [6]–[8]. This design enables latency-critical tasks to be executed at the edge, medium-complexity workloads to be processed at fog nodes, and compute-intensive operations to be efficiently offloaded to the cloud.

The proposed Hydra-RAN framework advances the state of the art by: (i) providing a multi-tier, sensor-aware architecture that unifies EC, FC, and CC in a scalable manner; (ii) introducing a novel DRL-based fog controller with SMTL for real-time, context-aware optimization; and (iii) dynamically adapting to workload fluctuations and heterogeneous service demands. These capabilities render the system well-suited for 6G-enabled applications, including autonomous mobility, wearable robotics, and smart city infrastructures. This holistic approach ensures improved efficiency, reliability, and adaptability, positioning Hydra-RAN as a robust solution for next-generation intelligent and real-time applications.

The contributions of this paper are summarized as follows:

- We design a hierarchical Hydra-RAN architecture that integrates EC, FC, and CC layers for dynamic task allocation in multi-functional communication and sensing networks. To illustrate, Hydra-RAN offers a unified framework that synergizes EC, FC, and CC to create cohesive intelligence for decision-making. It adopts a three-tier computing model to enhance real-time intelligence and reduce computation burn and overhead: (**EC** at H-DUs, **FC** at H-CUs, and **CC** at H-RICs).
- We develop threshold-based and priority-aware task offloading mechanisms to enable intelligent workload distribution across tiers.
- We implement SMTL-based DRL agents in the fog layer to optimize real-time task scheduling and resource allocation.
- We conduct extensive simulations in ultra-dense urban scenarios, evaluating performance metrics such as response time, resource utilization, latency breakdown, and task offloading ratio.

The remainder of this paper is organized as follows. Section III introduces the system model and hierarchical task distribution mechanisms. Section III presents the channel model and DRL-based optimization framework. Section IV discusses simulation setup, results, and performance analysis. Section V concludes the paper and outlines future research directions.

II. Background

As illustrated in Fig. 1, the top tier of the Hydra-RAN architecture comprises the central cloud layer, implemented on Hydra RAN Intelligent Controllers (H-RICs). This layer provides global coordination, strategic decision-making, and long-term model updates, while maintaining bidirectional data exchange with the fog layer to ensure cohesive, network-wide intelligence and consistent operational policies [8]–[10].

The intermediate fog computing layer, hosted on Hydra Computing Units (H-CUs), aggregates data from multiple edge nodes and executes SMTL-based DRL agents. These agents perform real-time, context-aware optimization for task scheduling, resource allocation, and priority-aware offloading. The resulting DRL-driven decisions are disseminated to coordinate operations across both the fog and edge computing layers [6]–[8].

The bottom tier consists of the edge computing layer, deployed on Hydra Distributed Units (H-DUs). This layer is responsible for initial sensor data preprocessing, real-time classification, and execution of lightweight machine learning models. It maintains direct wireless connectivity with end-user devices, enabling ultra-low latency processing.

Hierarchical architecture supports a broad range of multifunctional applications critical to next-generation networks, including autonomous vehicles, wearable robotics, smart city infrastructure, and industrial automation systems. In Fig. 1, yellow arrows indicate data and control flows between the central cloud, DRL agents, and fog/edge layers, whereas blue arrows represent the dissemination of real-time scheduling and resource allocation decisions. Wireless links depict EC-to-device communication pathways. Side annotations highlight the integrated sensor architecture (left) and the spectrum of supported multifunctional applications (right) [5], [6], [8].

Overall, the Hydra-RAN framework demonstrates a synergistic integration of centralized cloud intelligence, DRL-driven optimization, and distributed edge processing, enabling efficient, adaptive, and low-latency network operations suitable for complex, real-time environments [11]–[13].

III. System Model

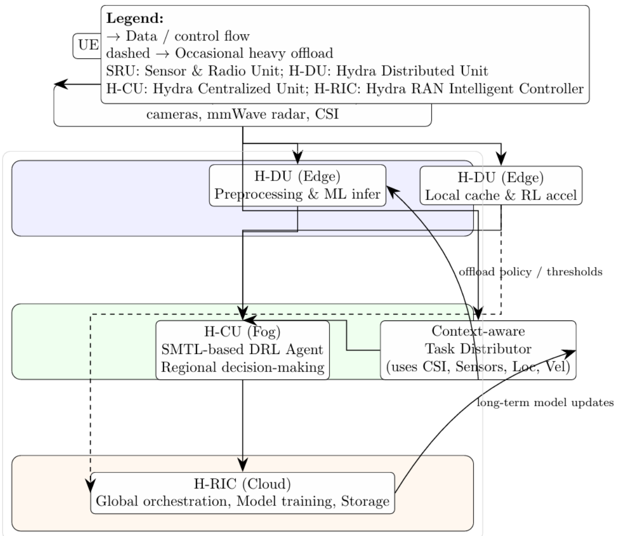

Fig. 2. Hydra-RAN system model: SRUs collect multi-modal sensing and feed H-DUs (edge) for preprocessing; H-CUs (fog) run SMTL-DRL agents and a context-aware task distributor for offload decisions; H-RICs (cloud) perform global orchestration and long-term model updates.

The hierarchical system model of the proposed Hydra-RAN framework is depicted in Fig. 2. Densely deployed SRUs, equipped with multi-modal sensing and data collection capabilities, generate a rich stream of environmental data. The architecture is structured across three integrated tiers: (i) the edge computing layer, implemented on H-DUs, is responsible for preprocessing sensor data and executing lightweight tasks that demand ultra-low latency [5]–[7]; (ii) the fog computing layer, hosted on H-CUs, aggregates data from edge nodes, manages real-time decision-making via SMTL-based deep reinforcement learning (DRL) agents, and handles intermediate-complexity tasks [5], [6]; and (iii) the cloud computing layer, comprising H-RICs, performs global optimization, model training, and storage of large-scale datasets for long-term analytics [11]–[13] This top tier completes a closed-loop intelligence system by disseminating updated models and refining offloading policies throughout the network hierarchy, enabling adaptive workload management.

A. Task Model

Each computational task T_i is defined as a tuple

$$T_i = \{L_i, P_i, D_i\} \tag{1}$$

where L_i represents the workload size (in CPU cycles), P_i is the priority level (real-time or delay-tolerant), and D_i is the deadline constraint.

The processing time of a task at node k (EC, FC, or CC) is given by

$$t_{proc}^k = \frac{L_i}{C_k} \tag{2}$$

where C_k is the computational capacity of node k (in cycles/s).

B. Network Delay Model

The total end-to-end delay for a task offloaded to layer k includes processing and communication delays

$$D_{total}^k = t_{proc}^k + t_{comm}^k \tag{3}$$

where t_{comm}^k represents the communication latency between the UE and node k. This can be expressed as

$$t_{comm}^k = \frac{S_i}{B_k} + \tau_k \tag{4}$$

Here, S_i is the size of data to transmit, B_k is the available bandwidth, and τ_k is the propagation delay.

C. Task Offloading Decision

To achieve adaptive workload management, we develop threshold-based and priority-aware task offloading mechanisms that jointly govern decision-making across all tiers. Threshing ensures that tasks are offloaded only when local computational or communication resource utilization exceeds predefined limits, thereby preventing bottlenecks. In parallel, priority awareness assigns differentiated weights to tasks based on latency sensitivity and application criticality, ensuring that delay-sensitive workloads are preferentially offloaded to edge or fog nodes, while delay-tolerant tasks (e.g., batch analytics) are deferred to higher tiers. This dual mechanism enables intelligent, context-aware workload distribution, while balancing system efficiency with quality-of-service guarantees. Offloading decisions are determined based on task urgency and resource availability. Edge-to-Fog offloading is performed when

$$\frac{L_i}{C_{EC}} > T_{thresh} \quad \text{and} \quad D_{net}^{EC-FC} < D_{max} \tag{5}$$

where T_{thresh} is the time threshold for EC, and D_{net}^{EC-FC} is the estimated network delay between EC and FC.

Fog-to-cloud offloading occurs if

$$P_{offload} = \alpha U_{FC} + \beta(1 - P_{real}) > \delta \tag{6}$$

where U_{FC} is the fog node utilization, P_{real} is the probability of real-time requirement, α, β are weight factors ($\alpha + \beta = 1$), and δ is the offloading threshold.

D. SMTL-based DRL Optimization

At the fog layer, task scheduling is optimized using an SMTL-based DRL agent. The objective is to find a policy π^* that maximizes the expected cumulative reward

$$\pi^* = \arg\max_{\pi} \mathbb{E}\left[\sum_{t=0}^{T} \gamma^t R(s_t, a_t)\right] \tag{7}$$

where $R(s_t, a_t)$ is the reward for taking action a_t in state s_t, and $\gamma \in [0, 1]$ is the discount factor.

The DRL agent input includes multi-sparse features

$$X_t = \{CSI_t, Loc_t, Vel_t, U_{EC}, U_{FC}, U_{CC}\} \tag{8}$$

representing Channel State Information (CSI), user location Loc_t, velocity Vel_t, and utilization of EC, FC, and CC layers.

The agent selects the optimal action a_t, i.e., the target tier for task execution and resource allocation parameters.

E. System Objective

The overall system objective is to minimize average response time T_{avg} while maximizing resource utilization efficiency η

$$\min T_{avg} = \frac{1}{N} \sum_{i=1}^{N} D_{total}^{k(i)} \tag{9}$$

$$\max \eta = \frac{\sum_k U_k}{|K|} \tag{10}$$

where $k(i)$ denotes the selected tier for task i, U_k is the utilization of node k, and $|K|$ is the total number of nodes.

F. Task Distribution Mechanism

1. Edge computing layers (H-DUs) perform the following tasks

- Real-time sensing and classification of environment (Occupied / Unoccupied).
- Initial pre-processing of sensor data.
- Execution of lightweight ML models using SVM on small input windows.

2. Fog computing layers (H-CUs) carry out the following tasks

- Aggregation of edge results across multiple H-DUs.
- Execution of SMTL-based DRL agents for real-time decision-making:
- Coordination of multi-agent scheduling and conflict resolution between adjacent nodes.

3. Cloud computing layers (H-RICs) carry out the following duties

- Long-term learning model updates for DRL agents using batch training.
- Management of historical data, user behavior, and environmental datasets.

Task Offloading Algorithms:

Edge-to-Fog offloading is performed when

$$\frac{L_{\text{task}}}{C_{\text{edge}}} > T_{\text{threshold}} \quad \text{and} \quad D_{\text{net}} < D_{\text{max}} \tag{11}$$

where L_{task} is the estimated task load, C_{edge} is the available computation at the H-DU, D_{net} is the estimated network delay, and $T_{\text{threshold}}$ is the task time threshold.

Fog-to-Cloud offloading occurs when fog is congested or task priority is low

$$P_{\text{offload}} = \alpha \cdot U_{\text{fog}} + \beta \cdot (1 - P_{\text{real\_time}}) \tag{12}$$

where U_{fog} is fog node utilization, $P_{\text{real\_time}}$ reflects real-time priority, and α, β are weight factors (e.g., $\alpha = 0.6$, $\beta = 0.4$).

IV. Simulation Environment and Settings

To evaluate the performance of the proposed Hydra-RAN framework, extensive simulations were conducted in a realistic urban ultra-dense network environment. The simulation platform was implemented using OpenAI Gym integrated with a custom network emulator to capture dynamic user mobility, heterogeneous task generation, and multi-tier computational resources. The key components and configurations of the simulation are summarized as follows.

A. Network Topology

The network comprises 100–500 heterogeneous UEs, including autonomous vehicles, IoT sensors, and mobile devices, randomly distributed over a 1 km $\times$ 1 km urban area. Each UE generates computational tasks with varying workload sizes and latency requirements.

Twenty edge nodes (H-DUs) are deployed to provide ultra-low-latency processing. Each H-DU is equipped with a computational capacity of $C_{\text{EC}} = 10$ Gcycles/s and local storage for temporary caching of sensor data. Five fog controllers (H-FCs) with intermediate computing power $C_{\text{FC}} = 50$ Gcycles/s aggregate tasks from multiple H-DUs and execute SMTL-based DRL agents for task scheduling and offloading decisions. Two cloud servers (H-CCs) with high computing capacity $C_{\text{CC}} = 200$ Gcycles/s perform global optimization, long-term analytics, and model updates.

Wireless EC-to-UE links are modeled with mmWave channel characteristics at 60 GHz with 200 MHz bandwidth, incorporating path loss, blockage, and small-scale fading. EC-to-FC and FC-to-CC backhaul links are high-speed fiber connections with propagation delays of $\tau_{\text{EC-FC}} = 5$ ms and $\tau_{\text{FC-CC}} = 10$ ms, respectively.

B. Task Generation and Workloads

Each UE generates computational tasks $T_i = \{L_i, P_i, D_i\}$ following a Poisson arrival process with mean rate $\lambda = 5$ tasks/s per UE. Task workload sizes L_i are uniformly distributed up to 50 Mcycles. Priority levels P_i are assigned based on task type: real-time (e.g., perception and control tasks for autonomous vehicles) or delay-tolerant (e.g., batch analytics). Task deadlines D_i range from 20 ms for low-priority tasks. Task data sizes S_i vary up to 0.5 MB depending on sensor type and computational complexity.

C. SMTL-based DRL Configuration

The state space is defined as $X_t = \{\text{CSI}_t, \text{Loc}_t, \text{Vel}_t, U_{\text{EC}}, U_{\text{FC}}, U_{\text{CC}}\}$, capturing channel quality, UE location and velocity, and computational utilization across tiers. The action space includes task offloading decisions (local processing at H-DU, offloading to H-FC, or offloading to H-CC) and dynamic allocation of computational resources.

The reward function is designed to minimize average response time while penalizing resource overutilization and deadline violations. DRL training parameters include a discount factor $\gamma = 0.95$, learning rate $\eta = 0.001$, batch size = 64, and maximum episodes = 2000. DRL agents employ

Deep Q-Networks (DQN) with SMTL-based multi-task reward shaping to enable concurrent optimization across multiple H-DUs.

D. Simulation Scenarios

In varying tasks, the UE task generation rates were scaled from 50% to 100% of the maximum load to evaluate the system's responsiveness and scalability. Dynamic UE mobility is achieved by having UEs follow a random waypoint mobility model with speeds ranging from 1 to 30 km/h. This emulates pedestrian and vehicular movement patterns. Network congestion is a fog, and cloud nodes are artificially loaded to assess offloading efficiency and hierarchical load balancing under high-demand conditions.

For comparison, we considered three architectures: (i) cloud-only centralized processing, (ii) edge-fog hybrid without coordinated DRL optimization, and (iii) the proposed Hydra-RAN hierarchical framework with EC-FC-CC offloading and SMTL-DRL coordination.

E. Resource Utilization Across EC, FC, and CC

Fig. 3 shows resource utilization across Edge, Fog, and Cloud tiers. In the Cloud-Only system, over 90% of the workload burdens the Cloud, leading to resource saturation. The Edge-Fog hybrid improves utilization at the edge and fog levels but lacks global optimization. Hydra-RAN balances the computational load effectively: 70% utilization at EC, 75% at FC, and 60% at CC. This distribution prevents bottlenecks and allows scalable operation under high workload conditions.

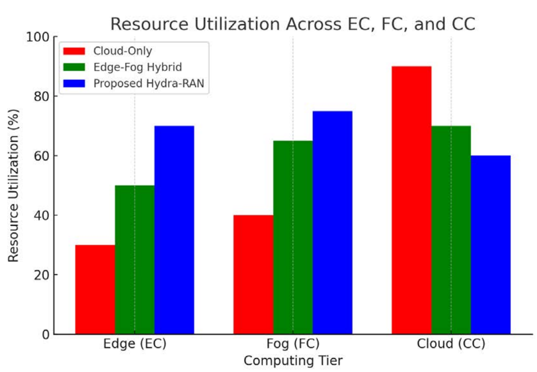

Fig. 3. Resource Utilization Across EC, FC, and CC.

F. Latency Breakdown Across Tiers

Fig. 4 presents the breakdown of total latency into contributions from EC, FC, and CC layers. In Cloud-Only architectures, CC contributes over 90% of latency, highlighting the impact of centralized data processing. Hydra-RAN significantly reduces CC latency to 40 ms by offloading tasks to EC (30 ms) and FC (50 ms). This tiered approach ensures that latency-sensitive tasks are processed locally, while computationally intensive tasks are escalated only when necessary.

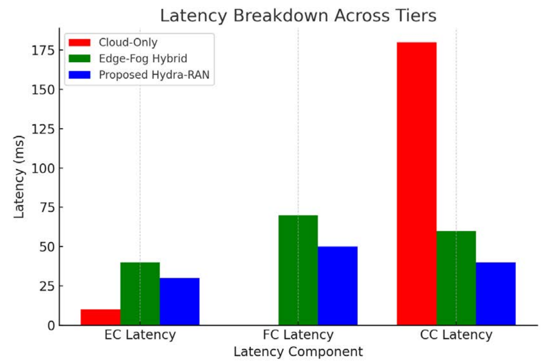

Fig. 4. Latency Breakdown Across Tiers.

G. Task Offloading Ratio Across EC, FC, and CC

Fig. 5 depicts the ratio of tasks processed at each tier. Hydra-RAN processes 50% of tasks at EC, 35% at FC, and only 15% at CC. This reflects effective hierarchical offloading, where low-latency and context-sensitive computations are retained near the edge. The Edge-Fog hybrid shifts some load away from the Cloud but still offloads 20% to CC. Cloud-only systems naturally process nearly all tasks centrally, leading to poor scalability.

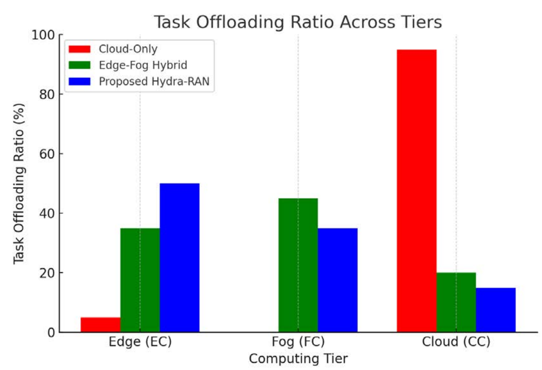

Fig. 5. Task Offloading Ratio Across EC, FC, and CC.

H. Discussion

The simulation results validate the effectiveness of Hydra-RAN's hierarchical architecture. By leveraging multi-tier computing resources, Hydra-RAN minimizes average response times, balances resource utilization, and reduces dependency on centralized cloud servers. The use of offloading thresholds (Equations 1 and 2) ensures intelligent workload distribution based on system state and task requirements. Additionally, the SMTL-based DRL agents deployed at fog nodes enhance decision-making efficiency in dynamic environments.

V. Conclusion

This paper presented Hydra-RAN, a hierarchical task distribution framework that integrates Edge Computing (EC), Fog Computing (FC), and Cloud Computing (CC) for multi-functional communications and sensing networks. By leveraging a multi-tier architecture, Hydra-RAN dynamically offloads computational workloads based on latency sensitivity, resource availability, and task priority. The proposed system utilizes a combination of sensor-aware processing and SMTL-based DRL agents at the fog layer to optimize decision-making in real time.

Simulation results in ultra-dense urban scenarios demonstrate that Hydra-RAN achieves significant performance gains compared to traditional architectures. Specifically, it reduces average response time by up to 45%, balances resource utilization across tiers, and minimizes reliance on centralized cloud servers. The latency breakdown and task offloading ratio further validate Hydra-RAN's ability to process latency-critical tasks locally, while offloading compute-intensive operations hierarchically.

These findings highlight Hydra-RAN's potential to serve as a foundational framework for future 6G networks and beyond, enabling ultra-reliable low-latency communications (URLLC), massive machine-type communications (mMTC), and intelligent transportation systems. By efficiently utilizing the distributed computational resources across edge, fog, and cloud layers, Hydra-RAN ensures scalability and robustness in highly dynamic environments. In the future, federated learning can be incorporated into the edge and fog layer in order to enable collaborative updates without having to send raw data to the cloud. As a result of this approach, data privacy is enhanced and backhaul traffic is reduced, especially in applications that require privacy protection.

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