Hydra-RAN: Multi-Functional Communications and Sensing Networks for Collaborative-Based User Status

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***Abstract*—Conventional RANs typically adopt a one-size-fits-all approach, which limits their effectiveness in responding to the varying conditions inherent in dynamic modern environments. The rigid nature of these systems necessitates extensive manual tuning and configuration, which is both time-consuming and expensive. Therefore, there is an urgent need to develop an innovative network that combines diverse networks, services, and modern technology into a cohesive infrastructure. This convergence is essential for providing multi-faceted cooperation, cohesive functionality, and meeting contemporary applications in dynamic environments. The Hydra radio access network (H-RAN) has been conceptualized as a comprehensive platform. This innovative design aims to integrate all existing networks and services, establishing a cohesive environment where they can operate concurrently. H-RAN seeks to break down silos by fostering collaboration among diverse networks, facilitating seamless interoperability. This paper introduces a novel paradigm of H-RAN multi-faceted cooperation architecture that incorporates a dense deployment of sensor and radio units (SRUs) that work collaboratively to optimize user status decisions. In addition, we introduce inter-element cooperation in a cooperative multi-sparse input/multi-task learning-based federated learning paradigm, known as (C-SMTL), which is an integral component of the AI/ML D-engine allowing H-RAN components to align their objectives toward common goals, thereby optimizing learning outcomes. This collaborative focus paves the way for a more robust and efficient machine learning (ML) framework. A key highlight of the simulation findings is the approach's ability to increase classification accuracy by an impressive 95% while maintaining reliability.**

***Index Terms*—Hydra radio access network (H-RAN), Multi-Functional networks, Perceptive networks, Heterogeneous data, AI/ML engines, Accurate user status, and Cooperative multi-sparse input/multi-task learning-based federated learning (C-SMTL).**

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I. Introduction

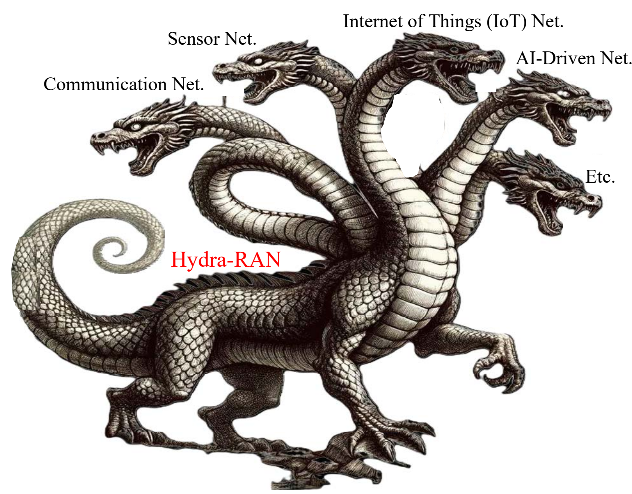

Figure 1: H-RAN evolution represents a transformative shift in network architecture, emphasizing the integration of multiple networks and technologies to create a cohesive ecosystem that supports diverse applications. This network is not only technologically advanced, but it is also resilient and adaptable to changing conditions. This holistic approach not only consolidates functionalities but also optimizes resource utilization across the network.

With the continual emergence of evolving applications and increased reliance on advanced technologies, 5G may not be able to fully address future requirements and demands. The inadequacy of 5G in certain contexts highlights the necessity for networks that can dynamically respond to diverse and rapidly changing conditions. Conventional radio access networks (RANs) are characterized by predominantly monolithic architectures that hinder their flexibility and scalability, preventing effective adaptation to varying user demands and rapid changes in environmental conditions. This rigidity

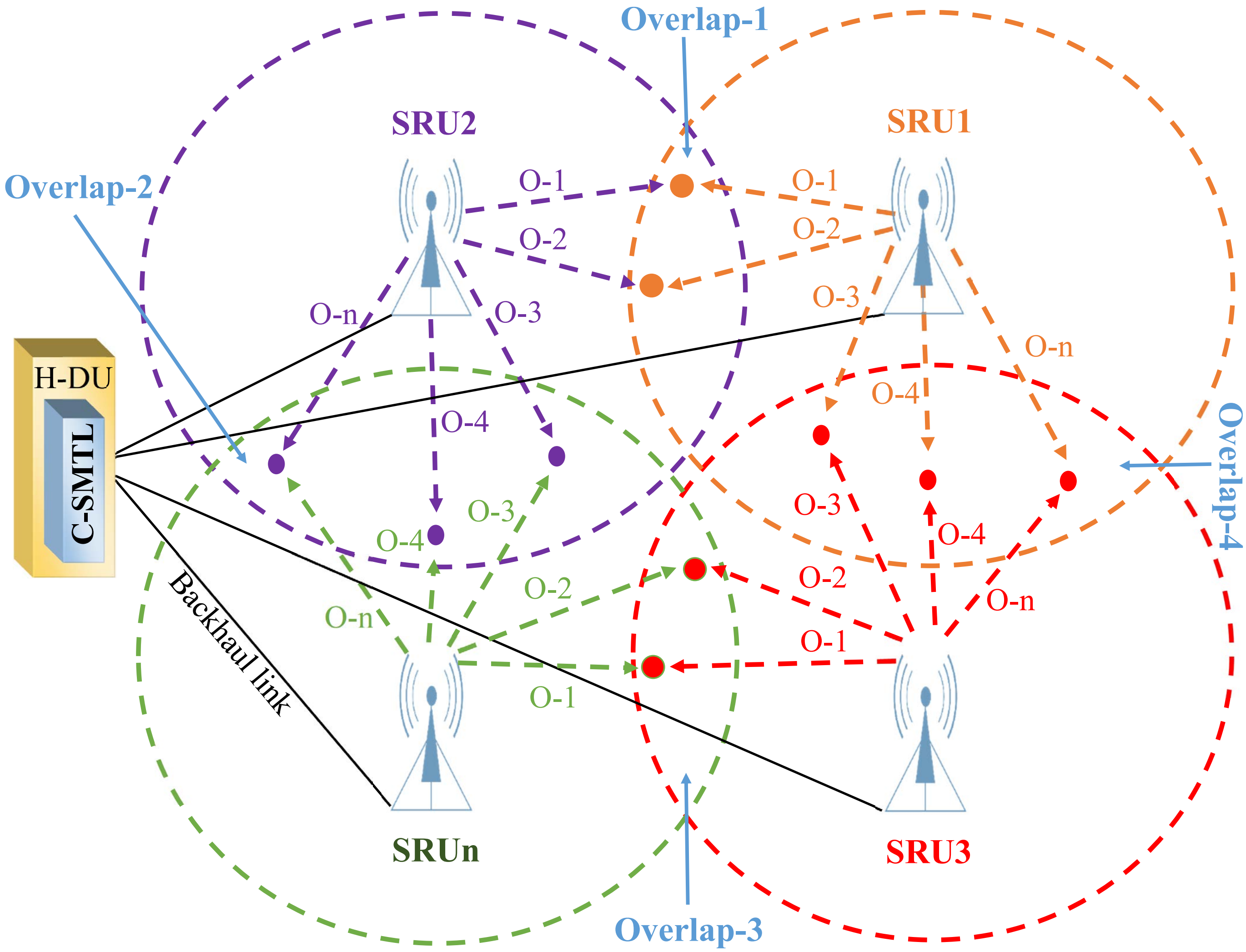

Figure 2: H-RAN network topology: The disaggregated architecture of sensor and radio units (SRUs) and Hydra distributed unit (H-DU) perceptual networks facilitates heterogeneous network deployment. Overlapping areas between SRUs can improve the accuracy and reliability of information gathered about objects or events. Cooperation between multiple SRUs facilitates effective monitoring and comprehensive data sharing in wireless networks. This collaboration enables the SRUs to combine their resources and insights, enhancing the overall network's observation capabilities and improving the accuracy of the data collected.

compromises real-time modifications, which are critical in the evolving landscape of contemporary applications. Therefore, there is an urgent need for an innovative and cohesive network integrating various networks, services, and modern technologies. This is crucial for streamlined operations and supporting the growth of interconnected applications in today's digital environment. A unified infrastructure plays a pivotal role in facilitating interconnected applications' growth. This is essential in today's digital landscape, where applications require seamless communication and data exchange to operate effectively across various platforms. Hydra radio access networks (H-RANs) are an innovative platform designed to meet future network demands by establishing a unified, versatile, and intelligent network. This evolution seeks to combine communication networks, sensor networks, edge computing (EC), the internet of things (IoT), distributed ledger (DL), automated driving (AD), vehicle-to-everything (V2X), etc., enabling a cohesive operation that meets the diverse demands of these technologies. This integration facilitates seamless data sharing and collaboration across various applications, ensuring that all components function harmoniously. H-RAN symbolizes a network architecture capable of adapting dynamically and accommodating a wide range of services and technologies. H-RAN's framework is expected to be central to the evolution of the communications and sensor ecosystem in the upcoming multi-functional network era [1], [2]. This architecture integrates extensive sensor data as well as AI/ML workflows across a wide range of diverse functional components, emphasizing and extending the concept of functional disaggregation for the next generation of sensory and radio access networks (NG-SRANs) [1], [2]. Moreover, in the H-RAN framework, the dense deployment of sensor and radio units (SRUs) is essential for providing adequate coverage to meet the growing demands of connected devices, reducing latency, and increasing data throughput. This paper proposes a novel H-RAN multi-faceted cooperation architecture that enables the accurate gathering of user status information for centralized control by Hydra distributed units (H-DU) [1], [2], including location, direction, speed, classification, weather condition, probability of blockage, communication parameters, etc. [1], [2]. By analyzing combined observations from multiple SRUs, H-RAN networks can provide a more detailed and precise representation of the network environment, significantly reducing the risk of errors associated with data reported by individual SRUs. Moreover, H-RAN multi-faceted cooperation strategies minimize the individual overhead experienced by individual nodes, which reduces the burden on a single SRU by sharing monitoring tasks and consolidating observations. In addition to SRU cooperation, we introduce cooperative multi-sparse input/multi-task learning-based federated learning (C-SMTL), which is an integral component of the AI/ML D-engine [1], [2]. This innovative approach fosters collaboration among various components within H-RAN edge/cloud networks, enabling the execution of diverse SMTL tasks according to real-time input features. By pooling data through different network components, computation sharing facilitates collaboration among network components and enables the aggregation of model updates and shared workloads [5]–[8]. The combination of SRUs and SMTL cooperation forms the core of H-RAN multi-faceted cooperation, which enables many complementary technologies. It is worth mentioning that accurate user status extends beyond communication networks, affecting how various modern technologies function. By bolstering system accuracy and reliability, accurate status information becomes a cornerstone of success in diverse applications across multiple industries. For the sake of brevity, this study focuses exclusively on cooperation-based user status decisions, which is a critical aspect for making informed decisions within the various networks and services organized within the unified RAN, including communication networks, sensor networks, EC, the IoT, DL, AD, V2X, monitoring, security, etc.

II. H-RAN MODEL

As shown in Fig. 2, we consider an outdoor environment with an H-RAN network [1], [2] that consists of multi-access SRUs. SRUs can gather real-time information about users and their surroundings using a variety of sensor technologies. In dense network environments, SRUs are designed to function collaboratively. In such collaborative networks, multiple SRUs can communicate and share information regarding network conditions and user status, where UE_k, and $K = \{1, 2, 3 \ldots, n\}$. In the H-RAN architecture, data collected by the SRUs is transmitted to the H-DU. Upon reaching the H-DU, the data undergoes processing through multiple layers, including communications layers, sensor layers, and AI/ML D-engine layers. Each layer has been designed to address particular aspects of information. C-SMTL is a part of the AI/ML D-engine which utilizes a cooperative paradigm that emphasizes cooperation to unlock the potential of H-RAN edge/cloud networks in the execution of distributed SMTL tasks. Specifically, C-SMTL leverages open FH links for data and model sharing with other C-SMTLs. This intelligent cooperation can improve ML model performance with a reduction in energy consumption and latency.

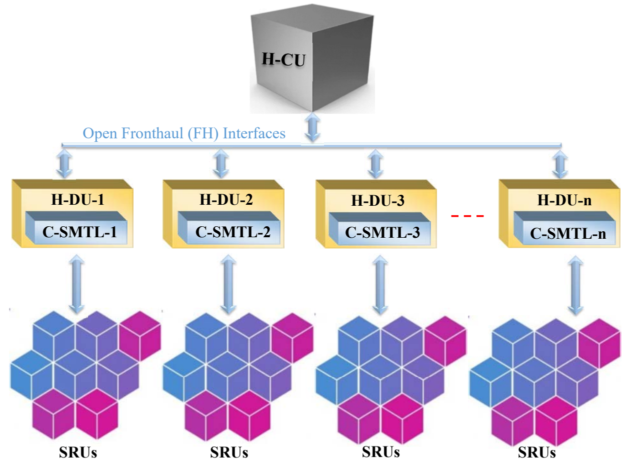

Figure 3: The proposed C-SMTL architecture goes beyond traditional global aggregation methods by fostering closer collaboration among network components, enabling richer interaction between various components. C-SMTL significantly broadens cooperation among distributed nodes, facilitating data and model sharing among participants. This shift allows local nodes to work more effectively by leveraging insights gained from other nodes within the network, thus promoting a collective learning approach that is more robust to individual data discrepancies and facilitating better overall performance.

Moreover, in a dense cooperative SRU network, the H-DU assigns a unique index to each connected user equipment (UE). This unique indexing enables the network to distinguish between users irrespective of the overlapping SRUs in the vicinity. For instance, as shown in Fig. 2, the network model consists of four SRUs with at least two overlaps between each SRU. SRUs are strategically placed to provide overlapping coverage areas. This means that multiple SRUs can serve the same user or region, offering redundancy and multiple communication paths. In other words, SRU_o possesses the potential to cooperate to serve common UEs. According to this definition, the network can be represented by an arbitrary diagram $H = \langle \mathrm{SRUs}, \mathrm{SRU}_o \rangle$ where $\mathrm{SRU}_o \subseteq \mathrm{SRUs}$, where SRUs represent the cluster of SRUs controlled by H-DU, and SRU_o is the overlapping SRUs group. In dense SRUs, a UE can simultaneously reach multiple SRUs located in its vicinity. However, for operational efficiency, it is assumed that a UE can be associated with only one SRU at any given time. While the UE is connected to one primary SRU, the overlapping SRUs continue to monitor and track the connected UE. This monitoring capability provides valuable insights into the UE's status, location, and signal conditions, enabling the network to assess and respond to changes in real-time. Consider that the local posteriors formed at SRU nodes are represented as the densities of labeled random finite sets $\{\boldsymbol{X}_1, \ldots, \boldsymbol{X}_{m_s}\}$, where m_s denotes the number of sensors in each SRU. In this framework, it is assumed that the labels corresponding to identical objects in each labeled random finite set are consistent across the network. Any potential label mismatch issues are presumed to be effectively managed by H-DU's centralized architecture. Assume that the FoV of the s_{th} sensor by $\mathrm{FoV}_s \in \mathbb{X}$, and its detection probability can be formulated as

$$\begin{aligned}\Pr(X_2^{(\rho)} = \varnothing \,\Big|\, X_1^{(\rho)} = \varnothing) \\ = 1 - \frac{\exists_{k|k-1}^{(\rho)} \left[1 - \langle p_{k|k-1}^{(\rho)}, p_{D_2} \rangle (\mathrm{FoV}_2 \backslash \mathrm{FoV}_1)\right]}{1 - \exists_{k|k-1}^{(\rho)} \langle p_{k|k-1}^{(\rho)}, p_{D_2} \rangle (\mathrm{FoV}_2 \backslash \mathrm{FoV}_1)},\end{aligned} \tag{1}$$

where X represents a labeled random finite set of multi-object states for which there can be more than one element with the same label, ρ is target label parameters, $\exists^{(\rho)}$ indicates the probability that the target exists by the label (ρ), $\exists_{k|k-1}^{(\rho)}$ denotes the probability of existence at the time $k|k-1|$, $p^{(\rho)}$ denotes the single-object density conditional on its existence, p_{D_2} represents the detection probability of each target within the field of view of the s_{th} sensor $\mathrm{FoV}_s \in \mathbb{X}$. If the two fields of view are completely separate, then $\mathrm{FoV}_2 \cap \mathrm{FoV}_1 = \varnothing$. Thus, $\mathrm{FoV}_2 \backslash \mathrm{FoV}_1 = \mathrm{FoV}_2$. Thus, the probability of existence of target (ρ) at SRU_2 $s = 2$ can be formulated as

$$P(\exists) = \frac{\exists_{k|k-1}^{(\rho)} [1 - \langle p_{k|k-1}^{(\rho)}, p_{D_2} \rangle (\mathrm{FoV}_2 \backslash \mathrm{FoV}_1)]}{1 - \exists_{k|k-1}^{(\rho)} \langle p_{k|k-1}^{(\rho)}, p_{D_2} \rangle (\mathrm{FoV}_2 \backslash \mathrm{FoV}_1)}, \tag{2}$$

As depicted in Fig. 2, in scenarios where certain SRUs face constraints such as blockage from specific angles or limited sensing range, cooperative sensing allows the system to compensate for these limitations. This is achieved by leveraging data from overlapping field of view (FoV) SRUs with complementary capabilities, capturing information from diverse perspectives, and expanding coverage areas.

As shown in Fig. 3, the Hydra central unit (H-CU) is responsible for overseeing higher layers of the protocol stack and ensuring coherent communication between the core network and the SRUs through direct interaction with the H-DUs. This management role includes guiding data management tasks, making strategic decisions, and optimizing network resource allocation [1].

A. Cooperation Among SRUs

In a dense deployment of SRUs, cooperation among overlapping and nonoverlapping SRUs is structured to enable effective data-sharing channels, where selected insights can be communicated to the H-DU. This targeted sharing ensures that only pertinent data is relayed, thereby optimizing decision-making processes while minimizing bandwidth usage. Through these shared data streams, the central H-DU can make informed decisions based on a comprehensive view of the network's conditions. By collectively pooling their observations, the SRUs can provide a higher-quality dataset to the H-DU for processing, leading to more accurate modeling and analysis of the network environment. Strategic placement of SRUs in overlapping coverage areas is critical to their design and deployment. This arrangement allows multiple SRUs to serve the same user or geographical region, thus creating redundancy in data collection. This redundancy ensures that even if one SRU fails or experiences interference, other SRUs can maintain service continuity and provide alternative data sources. Cooperative data sharing enabled by overlapping SRUs is also advantageous for optimizing H-DU decision-making processes. The aggregation of diverse observations from SRUs allows for a more comprehensive understanding of the network environment [7], [8].

B. Cooperative Multi-Sparse Input/Multi-Task Learning-Based Federated Learning (C-SMTL)

Indeed, conventional networks struggle to adapt to rapid and frequent changes in network environments due to their inherent limitations. They often rely on (a one-size-fits-all solution), which is static solutions and lacks the sophisticated perceptive capabilities provided by modern technologies, such as AI and sensors. This results in a rigid approach that cannot effectively address the nuanced and dynamic nature of current networking demands. The absence of adaptive capabilities limits their ability to adjust in real time, thus compromising their overall performance. The H-RAN is set to revolutionize conventional networks by comprehensively incorporating AI technologies across all network components. This evolution enables H-RAN to deliver a broad and adaptive range of solutions (tasks), facilitating real-time adjustments based on changing network conditions. This flexibility allows the network to dynamically modify its operational approach, switching between different tasks as network conditions evolve [1], [2]. The SMTL is designed to select, implement, and switch between a multi-task, each task is tailored to a specific network condition. Each selected task represents the optimal solution from a list of recommended solutions, namely "Tasks", according to input online sensing data input and communication parameters. SMTL offers the ability to switch between different tasks seamlessly, depending on fluctuations in network conditions. This adaptability is vital as it ensures that the network can instantaneously respond to changes.

In this study, the SMTL model [2] is implemented for cooperative federated learning. This technology enables efficient and scalable learning across multiple tasks in distributed environments, making it well-suited to applications where data is distributed across the edge, IoT, mobile devices, and the cloud. SMTL is inherently designed to address scalability challenges when dealing with multiple tasks simultaneously. This model ensures that diverse tasks can be managed concurrently without significant increases in resource demand [2]. It is particularly advantageous for applications involving fragmented data across different nodes. In these scenarios, federated learning avoids the pitfalls of centralized data gathering, which introduces latency. As part of this approach, cooperative federated learning is incorporated into SMTL to facilitate local training on each component of the model while still permitting collaborative improvements to the global model. Moreover, the C-SMTL framework addresses the severe heterogeneity challenges typically faced in distributed data environments, allowing for more context-aware models that remain aligned with varying data distributions across different tasks. The C-SMTL paradigm is designed to significantly expand cooperation dimensions and improve collaboration among participating entities, enabling them to learn efficiently from their distinct datasets while sharing valuable insights across the network. These mechanisms include data sharing, computation sharing, model sharing, and decision-making sharing [5], [6]. The C-SMTL paradigm utilizes links and opens FH interferences among H-RAN networks, devices, servers, and infrastructure. Enhances connectivity and interaction among various components within edge and cloud networks. This interconnectedness enables seamless data flow and model sharing between distributed units, fostering collaboration essential for optimizing ML outcomes. Although the C-SMTL paradigm enables many synergistic technologies, only a few are investigated in this study for brevity. As illustrated in Fig. 3, we investigate multi-SRU cooperation due to its substantial influence on improving user status accuracy by providing diverse and alternative sources of information for H-RAN networks.

III. Simulation And Results

In this section, simulations are performed to evaluate the performance of the proposed model using different simulation methods, including the ViWi dataset [9], the InSite ray-tracing software [10], OpenAI Gym [11], and the Python programming platform. We simulate an H-RAN scenario where a dense heterogeneous network composed of four SRUs is evenly distributed, and different user densities are deployed randomly. All SRUs are located within H-DU's control area and each SRU is equipped with sensors and communication units. We consider an H-RAN architecture [1], [2] for multi-access cellular networks of SRUs. This network is comprised of a serving SRU and at least two coverage-overlapping SRUs. The SRU is located at a distance of $d_[n]$ from the UE and they are scattered randomly within the coverage area. For coverage overlap, the cell radius is set to $r > D/2$ and SRUs coordinate their interference and power efforts through centralized control mechanisms of H-DU [1], [2]. The duration of periodic feedback t_i reported by SRU_i, includes the UE_j information e.g., position $\mathbf{X}_j(x_j, y_j)$, and the distance between SRU_i and UE_j $\mathbf{D}_j(d_{\text{j,x}}, d_{\text{j,y}})$. The distribution of obstructions within the cell is modeled as a Poisson point process. By applying queueing theory, we derive blockage probability analytically. Afterward, interference statistics are derived using the blockage model, which incorporates spatial randomness in the location of blockages and UEs. Next, according to interference statistics, we define and derive the coverage probability of a UE. According to UE coverage, we calculate the probability of a UE's preamble being transmitted successfully. The C-SMTL model is implemented to broaden cooperation dimensions and improve collaboration within participating entities, permitting them to learn from their distinct datasets and share valuable insights across the network. In the evaluation of cooperative performance within a C-SMTL framework, ensemble classification accuracy serves as the key performance metric. This accuracy measurement evaluates how well the model performs across various tasks and datasets in a collaborative setting. The experimental setup utilizes OpenAI Gym [11]as the environment template, integrating it with Python TensorFlow for model training and evaluation. OpenAI Gym offers a flexible framework for creating and testing reinforcement learning algorithms, making it suitable for SMTL tasks where performance incentives can be modeled as rewards. TensorFlow provides the necessary tools to implement complex neural network architectures required for efficient learning. We evaluate the sum of the most recent 20 iterations from M = 200 iterations to determine the converged reward. In each iteration of the proposed algorithm, the SRU aims to establish an association with the UE that exhibits the most favorable channel conditions. This decision is influenced by various parameters, including channel reliability, UE perception via SRU, location, proximity of the UE to the SRU, etc. By prioritizing superb channel conditions and minimizing distances, UEs are better positioned to receive superior service. If an SRU cannot fulfill a user's request due to limitations such as blockage or interference, the algorithm forwards the request to another overlapping SRU. This redundancy in service availability enables continuous adaptability.

In the simulation, we assumed the probability of a blockage occurring only on one side between the primary associated station and the end user, which can be referred to as the line-of-side (LoS). Inherent blockage characteristics can explain the inverse relationship between user status classification accuracy and blockage probability. As blockage probability increases, the ability of the primary associated station to perceive user status is compromised, causing the associated station to struggle to effectively perceive user status, leading to low accuracy. The absence of a secondary station exacerbates the issue as the main station relies solely on its line of sight to the UE. Therefore, without an alternative station, this ability to perceive diminishes directly as blocking conditions worsen. Meanwhile, the proposed approach outperforms conventional methods by showing a stable accuracy rate of approximately 95% despite an increase in blocking probabilities. In the simulation setting, the user is assumed to be static while obstacles interact dynamically. The observed stability in classification accuracy can be attributed to three key factors: the dense deployment of SRUs, the overlapping coverage areas of these units, and their cooperative functionality. The overlap coverage between SRUs further enhances classification reliability. This overlap ensures that if one SRU experiences a service blockage, other overlapping SRUs can still provide consistent user information and maintain service continuity. Cooperation among SRUs allows overlapping SRUs to share information and resources, ensuring that there is a backup in the event of a disconnection between the primary SRU and the user.

The reason for this is that when the primary associated station encounters a blockage at a specific angle, the alternative SRU can maintain perception by exploiting a different angle of view. Such a mechanism ensures that the system can continue operating despite localized disturbances, providing a more stable connection and reducing outages. By employing intelligent routing and coordination among multiple stations, the network can dynamically adjust to changing environmental conditions, preserving service quality for users.

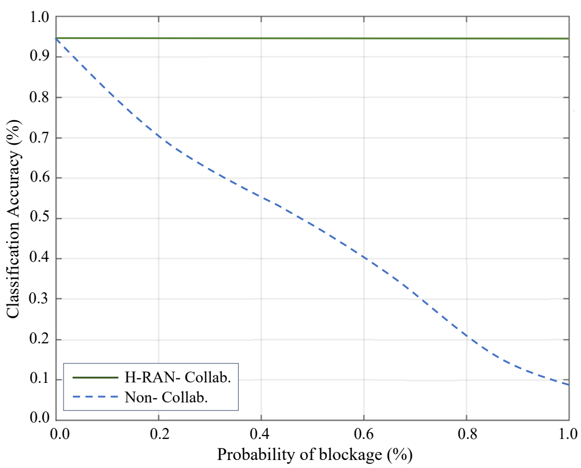

Figure 4: The classification accuracy of user status as a function of the probability of blockage.

IV. Conclusions

As emerging technologies evolve rapidly, traditional networks dedicated to specific applications or services are becoming increasingly insufficient. As these technologies advance, their demands on network infrastructures grow, highlighting the need for a more versatile and comprehensive network. In addition, to meet the escalating demand for wireless services, dense heterogeneous and cooperative networks are positioned as pivotal technologies for advancing networks. Sensor data within SRUs undergoes preprocessing to construct a comprehensive state representation that encapsulates current network conditions. Each SRU in the H-RAN architecture possesses its own FoV, delineating the spatial area for detection and communication with other devices. Moreover, the SRUs and C-SMTL paradigm strategically aim at broadening cooperation dimensions among entities. This framework encourages inter-element collaboration through selective data sharing and collective model training that maximizes the utility of shared insights without compromising each dataset's individuality. By utilizing the cooperation framework, entities can gain a holistic understanding of their operational environment. This comprehensive perspective fosters interconnectedness and adaptability, which are critical for navigating modern applications. User status accuracy extends beyond the realm of communication networks, influencing various technologies such as automated systems, monitoring platforms, IoT devices, etc. Since H-RAN is engineered to consolidate various networks and applications into a unified framework, accurate status information will enable systems to respond effectively to real-time data. For example, in automated vehicles, accurate user status can contribute to safety and decision-making quality, vital for preventing accidents and ensuring smooth operation. Our simulation results validate the effectiveness of the proposed approach in achieving a remarkable classification accuracy of 95% and ensuring consistent reliability.

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