Hydra Radio Access Network (H-RAN): Multi-Functional Communications and Sensing Networks, Adaptive Power Control, and Interference Coordination

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***Abstract*—The increasing urgency for innovative cohesive networks stems from the necessity to integrate various networks, services, and modern technologies. Researchers are progressing in integrating diverse networks, modern technologies, and services through cohesive networks to facilitate more streamlined operations. A unified infrastructure enables effective data sharing from various sources, breaking down silos that typically hinder data exchange. Hydra radio access networks (H-RANs) are designed to achieve researchers' ambitious objectives by seamlessly combining diverse networks and technologies into a single, intelligent, perceptive, and dense infrastructure. However, the proliferation of dense deployments of traditional wireless local area networks (WLANs) is significantly contributing to excessive power consumption and encountering substantial interference challenges. In this paper, we propose a novel collaborative approach utilizing the H-RAN perceptual network architecture for distance-based adaptive power control and interface mitigation. By harnessing this integration into a cooperative multi-sparse input/multi-task learning-based federated learning (C-SMTL) framework. The cooperative architecture adeptly addresses the challenges associated with dynamic power control and interference coordination. Simulation results show that our strategy significantly improves network performance. This is done by achieving high throughput capacity, reducing interference by 90%, and maintaining high efficiency even with increasing user density.**

***Index Terms*—Hydra radio access network (H-RAN), Perceptive networks, Multi-functional networks, Heterogeneous data, AI/ML engines, cooperative multi-sparse input/multi-task learning-based federated learning (C-SMTL), Interference coordination, and Adaptive power control.**

I. Introduction

Conventional networks are often hampered by their fixed configurations, which lack the flexibility to adapt to dynamic changes in network environments. This "one-size-fits-all" approach typically involves pre-configured settings that remain fixed, unable to respond effectively to variations in user demand, traffic patterns, or environmental changing conditions. Anticipating future demand requires self-learning RAN systems equipped with modern AI capabilities to autonomously adjust to changing network parameters and better serve future demands [1], [2]. Hydra radio access networks (H-RANs) represent a significant evolution in the telecommunications and sensor ecosystem landscape in anticipation of 6G deployment and beyond [1], [2]. The strength of H-RANs lies in their capability to merge various technologies, applications, services, and networks into a single, holistic intelligent network, extensively incorporating artificial intelligence (AI) into all network components. On the H-RAN platform, dense deployment of sensors and radio units (SRUs) is essential to provide adequate coverage and capacity for the growing number of connected devices in challenging MMW wireless communication scenarios [1]. However, dense deployments of SRUs can present significant challenges, including severe interference and high energy consumption [3]–[6]. Therefore, there is a pressing need to develop an approach designed to optimize system performance for distinct scenarios, as it allows for real-time responses to dynamic changes allowing for adjustments to changing conditions without significant delays.

To overcome this limitation, we propose a novel C-SMTL framework for adaptive power control and interference coordination over distance. In this scheme, sensors embedded within SRUs and throughout the network continuously capture real-time data concerning various parameters (e.g., user locations, distance, channel conditions, signal strength, etc.). This data undergoes preprocessing to generate a comprehensive representation of the network, encapsulating current network conditions, and enabling sophisticated network optimization [1], [2]. Afterward, C-SMTL leverages shared data and learning

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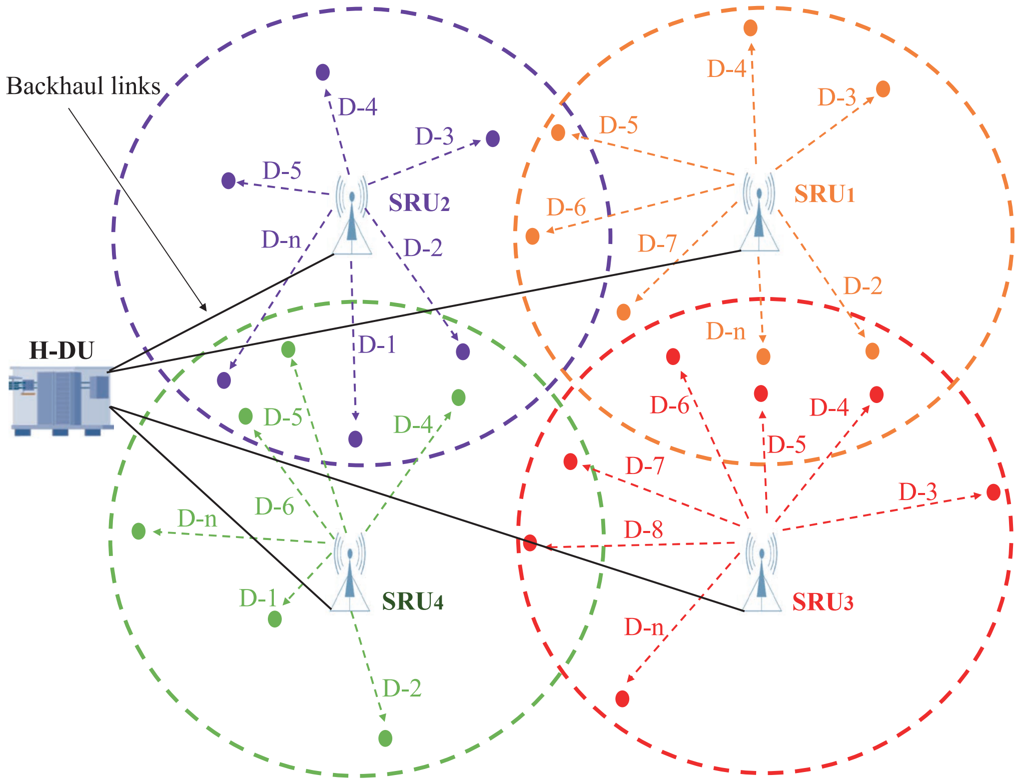

Figure 1: The disaggregated architecture of SRUs and Hydra distributed unit (H-DU) perceptual networks facilitates heterogeneous network deployment. Adaptive power control algorithms enable adaptive transmission strategies that optimize power allocation based on real-time network conditions (e.g. location, distance, interference from other SRUs.

across different tasks to dynamically optimize power control and interference. This synergy enables real-time decisions that respond to adaptive power control and interference in dense networks. This framework supports the complexities inherent in adaptive power and interference management within H-RANs, as it includes factors such as nonlinear relationships. Furthermore, the interference optimization challenge is framed as a mixed-integer nonlinear programming problem, which allows for the consideration of both continuous and discrete variables in the optimization process. For instance, in scenarios where the sender and receiver are in close proximity, it is beneficial to avoid using maximum transmission power. Instead, the system can intelligently adjust and lower the transmission power based on the actual distance between the sender and receiver. By reducing transmission power in close-range communications, the overall energy consumption of the system is optimized. When transmission power is lowered appropriately, the risk of cross-interference caused by multiple users operating simultaneously on the same frequency is greatly diminished. Simulation results show that our approach significantly improves network performance and achieves an impressive 90% reduction in interference levels while maintaining high efficiency, even as user density increases.

II. System Model

As shown in Fig. 1, in the system model, we consider an outdoor environment of H-RAN network topology [1], [2] with multi-access downlink cellular networks of SRUs. SRUs represent the key components in the H-RAN architecture that perform tasks beyond traditional communication. It acts as low-powered nodes providing coverage and capacity enhancements, encompassing both sensing and communication functionalities, enabling the network to process sensor data while also facilitating reliable wireless communication [1]. As shown in Fig. 1, 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 user equipment (UE). 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 Hydra distributed unit (H-DU), and SRU_o is the overlapping SRUs set. In dense SRUs, a UE can simultaneously reach multiple SRUs located in its vicinity. This spatial arrangement allows for enhanced connectivity options, as the UE has access to various SRUs capable of providing service. The transmission power rate between a user and its associated SRU is indeed shaped by a variety of factors. Key elements include the user's location, the distance to the SRU, and interference signals from the surrounding environment (e.g., adjacent SRUs). Therefore, an efficient optimization scheme can be achieved by leveraging real-time data collected from SRUs through a centralized controller, the H-DU [1]. For example, as illustrated in Fig. 1, each SRU has a distinct coverage area with four overlapping channels. In the real world, this overlapping might lead to severe interference among SRU_1, SRU_2, SRU_3, and SRU_4. By coordinating power adjustments across SRUs based on this overlapping interference information, the H-DU can ensure efficient energy usage while minimizing Co-channel interference [2]. As illustrated in Fig. 1, each SRU's coverage area is depicted as a circle centered on the SRU, with the radius expanding as the transmit power increases. In scenarios where a user resides within the overlapping coverage areas of multiple SRUs operating on the same channel, interference signals from these SRUs will be received, leading to a significant degradation in H-RAN performance. To quantify the interference within the network, a physical interference model is utilized to evaluate the interactions between user nodes and network links [3]–[6]. This model allows for the calculation of the signal-to-interference-plus-noise ratio (SINR) for a given user link within the prevailing interference environment. By assessing SINR, the model effectively captures the cumulative impact of interference among overlapping SRUs, providing a detailed understanding of how adjacent SRUs influence overall signal quality and network performance.

A. Channel Model

In distance-based adaptive power control, the transmit power is dynamically adjusted based on feedback from the UE_j and SRUs, utilizing data e.g., sensor readings, and channel quality indicators (CQI). 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 $\mathbf{D}_j(d_{j,x}, d_{j,y})$.

The received signal at the user $\text{U}E_j$ from the i_{th} SRUs is expressed as

$$\mathbf{y}_{\text{UE}_i} = \mathbf{h}_i\sqrt{\mathbf{p}_i}\mathbf{W}_i\mathbf{s}_i + \sum_{m=1, m\neq i}^{N_c} \mathbf{h}'_{i,m}\sqrt{\mathbf{p}_m}\mathbf{w}_m\mathbf{s}_m + \mathbf{n}_i, \quad (1)$$

where the first, second, and third terms describe the desired signal vector, the inter-SRUs interference vector, and the noise vector, respectively. $\mathbf{h}_i \in \mathbb{C}^{M^i \times N^i}$ corresponds to the desired channel matrix between SRU_i and UE_j , and $\mathbf{h}'_{i,m} \in \mathbb{C}^{M^m \times N^m}$ is the interference channel matrix describing channel gains between UE_j and SRU_i. $\mathbf{p}_i$ and $\mathbf{p}_m$ indicate the power allocation matrix for desired and interference signal vectors, correspondingly. $\mathbf{W}_i$ refers to the desired precoder, and $\mathbf{s}_i, \mathbf{s}_m \in \mathbb{C}$ refers to the transmitted signals from the desired signal i_{th}, and the inter-SRUs interference m_{th}, in that order. $\mathbf{n}^i$ represents the noise vector. The transmit power of transmitter SRU_i in time slot [t] is denoted as $P_i^{(t)}$, we can denote the power allocation of the SRU_i in time slot [t] as $\boldsymbol{p}_i^{(t)} = \left(p_1^{(t)}, \ldots, p_n^{(t)}\right)^{\mathsf{T}}$

In MMW channels, with accurate beamforming the gain of the line-of-sight (LoS) is the dominant path, hence the MMW channel model can be simplified to a single-path LoS model as follows:

$$\mathbf{h}_{b,i,j} = a(\theta_{b,i,j})\frac{\alpha_{b,i,j}}{\sqrt{L}(1+d_{i,j}^{\beta})}, \quad (2)$$

where $\mathbf{h}_{i,j} \in \mathbb{C}^{M\times 1}$ is the channel complex coefficient vector of UE_j user and SRU_i on b_{th} beam, $a(\theta_{k,i,j})$ is the steering vector, $\alpha_{b,i,j} \in \mathbb{C}N(0,\ \sigma^2)$ is the complex gain, and $d_{i,j}^{\beta}$ is the distance of the link (i, j) with path loss exponent β.

We propose an AI/ML D-engine-based SMTL model where H-DU jointly controls the beamforming vectors and transmit powers at the SRUs [1], [2]. According to the H-RAN standard, "Task_1" [2] the optimal beamforming vector is selected from a predefined codebook utilizing sensor data to aid AI/ML D-engine-based beam selection [1], [2]

$$C_{i,j}^{(1)} = \begin{cases} 1, & \text{if } (i,j) = \arg\max_{\text{m,n}} R_{\text{m,n}} \\ 0, & \text{otherwise.} \end{cases} \quad (3)$$

where $C_{i,j}$ is a label matrix, $R_{m,n}$ represent all beam pairs in the codebook, (i, j) corresponding to the optimal beam pair in the codebook.

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

The limited ability of conventional RANs to provide extensive collaboration among network components and adapt to real-time changing conditions, coupled with the rapid advancement of emerging technologies, intensifies their inadequacies [1], [2]. Addressing this inadequacy of traditional networks requires a fundamental shift towards more perception-driven, intelligent, predictive, responsive, and collaborative frameworks. H-RAN powered by SMTL is specifically structured to overcome conventional RAN inadequacies and rigid architectures. SMTL is notable for its ability to adapt to changing network environments. As input data characteristics shift, SMTL can seamlessly switch between a variety of tasks according to the current situation. Due to this ability, the model is able to address specific requirements that arise as a result of fluctuations in conditions [1], [2].

A. Distance-Based Adaptive Power Control

Adaptive power control contributes to improved spectral efficiency by minimizing wasted energy on unnecessary transmission power. By adjusting transmit power levels to match the actual requirements of the communication link, these algorithms maximize the use of the available spectrum and enhance the overall data throughput of the network. In this subsection, we introduce a distance-based power control approach, which is used to adjust the transmit power of the SRU to account for variations in the propagation environment and the distance between the SRU and the UE. The general idea behind our

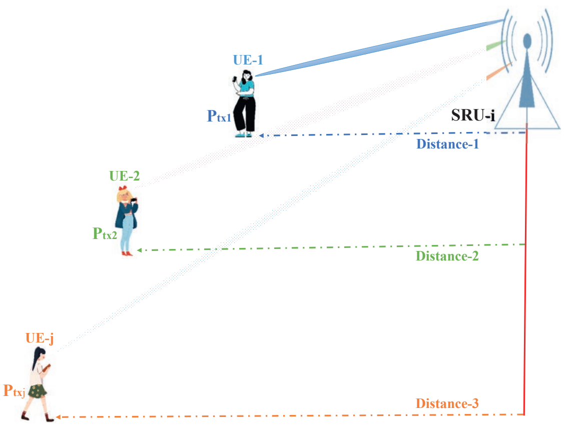

Figure 2: Distance-based dynamic power control utilizes the distances between transmitter and receiver nodes to adjust the transmission power accordingly.

approach is to ensure that the received signal strength at the UE is sufficient for reliable communication while minimizing energy waste and minimizing interference from neighboring SRUs. The transmit power is adjusted dynamically according to the estimated path loss between the SRU_i and the associated UE_j, which is determined by factors such as location, distance, terrain, and obstacles in the propagation environment, etc. As shown in Fig. 2, our models describe how signal strength attenuates as it propagates through space, based on the distance between the transmitter and the receiver. Assume that E_m refers to the minimum received energy sufficient to successfully decode the data transmitted by a transmitter. Accordingly, if the transmitter and receiver are distanced by a distance d, the minimum transmission energy needed to convey information is $E_m d^\beta$, where β represents the path-loss exponent. Thus, the total transmitter energy can be written as

$$\mathbf{P}^{\text{SRU}_i} = P_g E_m d^\beta, \tag{4}$$

where P_g is the actual transmission energy, E_m denotes the minimum received energy for a distance d with β path-loss exponent. The gains of each channel are assumed to be independent of each other, independent of spatial location, symmetric, and identically distributed [7]–[9]. The SINR of link b_{th} in time slot $[t]$ is a function of allocation power, which can be defined as

$$\text{SINR}_i^{(t)}(\boldsymbol{p}) = \frac{g_{i\rightarrow i}^{(t)} p_i}{\sum j \neq i g^{(t)} j \rightarrow i p_j + \sigma_n^2}, \tag{5}$$

where $g_{i\rightarrow j}^{(t)}$ defined as the downlink channel gain from SRU_i to UE_j in time slot t, $g_{j\rightarrow i}^{(t)}$ represents the channel gain from UE_j to SRU_i, and σ_n^2 is the additive white Gaussian noise. For the sake of simplicity, we assume that the channel coefficients are exponentially distributed in a Rayleigh fading environment. In such an H-RAN network, the channel model consists of small Rayleigh fading and large-scale path loss, thus the received downlink power signal can be described as [10], [11]

$$\mathbf{P}_{i,j}^{\text{UE}_j} = \mathbf{h}_{b,i,j} \mathbf{P}_{i,j}^{\text{SRU}_i} d_{i,j}^\beta, \tag{6}$$

where $\mathbf{h}_{b,i,j}$ represents the channel coefficient for that particular link between SRU_i and UE_j, $\mathbf{P}_{i,j}^{\text{SRU}}$ is the transmission power, d indicates the distance between the transmitter SRU_i and UE_j, and β refers to the path loss exponent.

The downlink power received by the UE_j from the SRU_i on the beam b_{th} at a given time t is defined as

$$\mathbf{P}_{i,j}^{\text{UE}}[t] = \mathbf{P}_{i,j}^{\text{SRU}}[t], |\mathbf{h}_{i,j}[t]\mathbf{f}_j[t]|^2, \tag{7}$$

where $\mathbf{P}_{i,j}^{\text{SRU}}[t]$ represents the transmitted power, $\mathbf{f}_j$ is the directional beamforming, and $\mathbf{h}_{i,j}[t]$ indicates the channel matrix between SRU_i and UE_i.

According to the transmit power $\mathbf{P}_{i,j}^{\text{SRU}}$ transmitted from SRU_i, we can estimate the received SINR for the UE_j served in SRU_i with transmit power interference from SRU_e at time step t can be formulated as

$$\text{SINR}_i[t] = \frac{\mathbf{P}_i^{\text{SRU}}[t]|\mathbf{h}_{\ell,i}[t]\mathbf{f}_i[t]|^2}{\sigma_n^2 + \sum_{e\neq i} \mathbf{P}_e^{\text{SRU}}[t]|\mathbf{h}_{\ell,e}[t]\mathbf{f}_e[t]|^2}, \tag{8}$$

where $\mathbf{P}_i^{\text{SRU}}$ and $\mathbf{P}_e^{\text{SRU}}$ correspond to SRU_i and SRU_e transmit power, respectively. We monitor the change in SINR_i as a result of the change in the beamforming vector. This changes according to the online report sensing environment. When the beamforming vectors b_{th} are selected for a given UE_j as specified in (3) [2], the H-DU also provides power control of that selected beam by changing the transmit power of the SRU_i to this UE_j according to UE_j e.g., location, distance and interference coordination with other SRUs.

As a result, the transmit power selection is governed by the location and distance of the UE_j relative to its associated SRU_i. Additionally, it accounts for interference coordination considering the impact on and from adjacent SRU_e. These factors collectively guide the optimization process for transmission settings, both of which are defined as [9]–[11]

$$\begin{aligned} \mathbf{P}_{i,j}^{\text{SRU}}[t] &= \min(\mathbf{P}_{\max}^{\text{SRU}}, \mathbf{P}_i^{\text{SRU}}[t-1] + \rho_i[t]), \\ \mathbf{P}_{e,j}^{\text{SRU}}[t] &= \min(\mathbf{P}_{\max}^{\text{SRU}}, \mathbf{P}_e^{\text{SRU}}[t-1] + \kappa_e[t]), \end{aligned} \tag{9}$$

where $\mathbf{P}_{\max}^{\text{SRU}}$ indicates the max transmit power, $\mathbf{P}_i^{\text{SRU}}$, and $\mathbf{P}_e^{\text{SRU}}$ are the actual transmit power for text SRU_i, and SRU_e, respectively. ρ_i represents the power control for the serving SRU_i and κe denotes the interference coordination on the interfering SRU_e.

IV. Distance-based Interference Mitigation

In a dense H-RAN, a user receives not only the signal from the associated SRU but also the interference signal from other SRUs and the noise from the environment. Therefore, the associated H-DU can determine the distance between the UE_j and the SRU_i as well as the overlapping SRUs. It can also calculate the interference level, and determine the RSSI required to meet the minimum RSSI threshold allocated to the UE_j. Thus, the AI/ML D-engine in H-DU can take several actions to avoid interference (e.g., reduce the transmission signal power according to distance, frequency switching, and SRU switching). Among the solutions proposed, we focus only on reducing interference through adaptive control of transmitted signal strength based on location and distance. The achievable downlink transmission rate of a link can be determined by the SINR of the current network status. Taking into account that the channel coefficient only reflects path loss, when UE_j is associated with SRU_i, the associated SINR can be expressed as

$$\mathrm{SINR}_{i,j} = \frac{\mathbf{P}_i d_{ij}^{-\beta}}{\gamma_j^{-i} + (\sigma_n^2)^i}, \tag{10}$$

We assume that the path loss depends on the Euclidean distance between SRU_i and UE_j, where P_i is the transmit power of SRU_i, $d_{ij}^{-\beta}$ indicates the free space path loss factor between SRU_i to UE_j, where d_{ij} represents the Euclidean distance between SRU_i and UE_j and β represents the path loss. γ_j^{-i} refers to the cumulative interference power received from nearby SRUs within its range, and $(\sigma_n^2)^i$ refers to the power of additive Gaussian noise in the environment.

According to [7]–[10] SINR can be influenced by the received signal strength indicator RSSI and channel separation. However, a high RSSI doesn't guarantee a good SINR if interference or noise levels are also high. Therefore, the appropriate RSSI for a given distance with increasing channel separation can reduce interference from neighboring channels or beams. The SINR as a function of RSSI and distance can be formulated as

$$\begin{aligned}\mathrm{SINR}_{i,j} =& D_{\mathrm{RSSI}} + 10\log d_{ij}^{-\beta} \\ & - 10\log\left(\sum_{x=1,x\neq i}^{N} \Delta\left(a_i, a_x\right) d_{ij}^{-\beta}\right) - \omega \\ &, \end{aligned} \tag{11}$$

where D_{RSSI} refers to the difference of RSSI received from the user from its associated SRU_i and interference SRUs based on the change in d_{ij} distance between SRU_i and UE_j, and the path loss β [9]–[11]. $\Delta\left(a_i, a_x\right)$ indicates the change in channel allocation, and $\omega = 10\lg\left(1 + \frac{\sigma n^2}{Ij^{-i}}\right)$ denotes the additive noise to the cumulative interference power it receives from other SRUs in its range.

According to the sensing information, if the distance from UE_j to SRU_i is less than the coverage radius of SRU_i, they are presumed to be associated together. Whenever UE_j is associated with SRU_i the H-DU adapts the allocated transmitted power based on the distance between the two parties. Therefore, without interference from other SRU_e, the received signal is only influenced by noise from the environment and distance attenuation between the user and the SRU_i. If two SRU coverage areas overlap, then the Euclidean distance between the two SRUs, SRU_i and SRU_e is given by.

$$d\left(\mathrm{SRU}_i, \mathrm{SRU}_e\right) = \sqrt{\left(x_a^i - x_a^e\right)^2 + \left(y_k^i - y_k^e\right)^2}, \tag{12}$$

where x_k and y_k correspond to the abscissa and ordinate of the SRU_e, respectively. The adjacency relationship between SRU_i and SRU_e can be expressed as a function of the effective coverage radius C_i, C_e, respectively by $d\left(\mathrm{SRU}_i, \mathrm{SRU}_x\right) < C_i + C_e$. Therefore, if SRU_i and SRU_e are considered overlapping coverage areas, then the value of $\psi_{i,j}$ is set to (1), otherwise (0), which indicates the associated relationship between SRU_i, and UE_j.

Thus, the achievable downlink transmission rate of UE_j can be calculated as [9]–[11]

$$C_{\mathrm{max,ij}} = \psi_{i,j} B \log_2(1 + \mathrm{SINR_{i,j}}), \tag{13}$$

Let assume ξ_j^{-i} as the inter-SRUs interference signal that UE_j receives from surrounding SRUs except for the currently associated SRU_i. Furthermore, ξ_j^n indicates the same channel interference that received by UE_j from the SRUs which is adjacent to SRU_i. Accordingly, the total interference received by UE_j from all adjacent SRUs can be characterized as

$$\xi_j^e = \sum_{n=1,n\neq i}^{n} \{a_{in} \Delta\left(r_i, r_e\right) \mathbf{P}_n g_{nj}\}, \tag{14}$$

where $\Delta\left(r_i, r_e\right)$ describes the channel relationship between SRU_i and SRU_e . If $r_i = r_e$, which implies that SRU_i and SRU_e occupy the same channel, then $\Delta\left(r_i, r_x\right)$ is set to (1), otherwise (0).

A. C-SMTL-Based Power Control And Interference Coordination

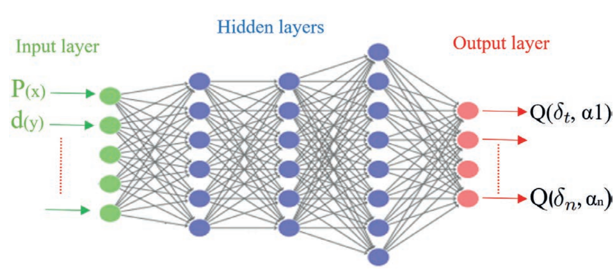

Figure 3: Structure of the deep Q-network-based AI/ML D-engine.

To minimize the computational complexity of the adaptive power control approach, we introduce AI/ML D-engine-based deep reinforcement learning (DRL) to optimize adaptive power control in dense H-RANs and obtain the most efficient joint optimization approach through training to learn the mapping between system inputs and optimal decisions. By implementing an event-driven mechanism of Q-learning, our approach effectively reduces the complexity of online learning in dynamic network environments while enabling adaptive decision-making. This approach facilitates the ability to respond to changing network conditions in real time. As a result of the offline strategy adjustment, s is the ability to respond to changing network conditions in real-time.

As shown in Fig. 3, the SRUs estimate the user's location and distance. The H-DU uses this information to choose the appropriate beamforming vector and then determines the strength of the transmitted signal power based on the location, distance, and interference with adjacent SRUs. As shown in Fig. 3, in the AI/ML D-engine the the deep-network $Q_{\pi}(\delta, a)$ is updated every time step, we formulate the state-action value function derived from the deep-network as

$$Q^{\star}_{\pi}(\delta_t, a_t) = \mathbb{E}_{\delta'}\left[r_{\delta} + \text{SINR}_{\text{tar[t]}} \max_{a'} Q^{\star}_{\pi}(\delta', a') \,\middle|\, \delta_t, a_t \right], \tag{16}$$

where δ is the discretization of the observations at time t e.g. location, distance, inter-cellular interference, inter-beam interference. A policy $\pi(\cdot)$ provides a mapping between the state of the environment δ and the action $a_t \in \mathcal{A}$ to be taken by the AI/ML D-engine to assess the impact on effective target $\text{SINR}_{\text{target [t]}}$ of the downlink transmission.

V. Results and discussion

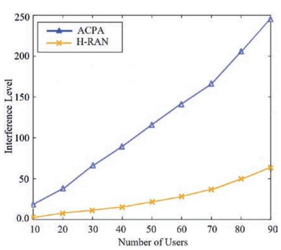

Figure 4: Interference level as a function of users.

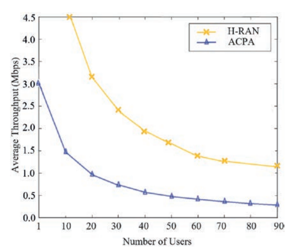

Figure 5: Average throughput as a function of users.

In this section, we run computer simulations to evaluate the performance of the proposed model under different settings, e.g., ViWi dataset, InSite ray-tracing software, and a Python programming platform. For model training and evaluation, OpenAI Gym serves as the environment template, integrated with Python TensorFlow.

Fig. 4 demonstrates that for four access points (APs) as the number of users increases, adjacent channel interference between APs increases. As can be seen from the results, the H-RAN algorithm is obviously superior to the ACPA algorithm [8]. The simulation results demonstrate a reduction in interference levels by 90% in our proposed algorithm. According to distance information, the SRU's transmit power is dynamically adjusted to optimize the received signal strength at the UE_j while minimizing interference with neighboring SRUs.

Fig. 5 shows the results for throughput as a function of UEs in the high interference scenario. When UEs are in a region of high interference, H-RAN achieves better performance compared to traditional ACPA schemes. This is because H-RAN-based adaptive power control continuously monitors the distance between the SRU_i and the UE_j. Accordingly, the $/textSRU_i$ transmit power is dynamically adjusted based on distance. This helps to prevent excessive interference by reducing the likelihood of interference from neighboring SRUs.

VI. Conclusions and future works.

To address power consumption and optimize interference in dense H-RANs, we propose a novel dynamic transmission power control strategy for SRUs. This approach leverages real-time sensor data and communication parameters to maintain the desired received signal strength while minimizing interference. We frame this interference optimization challenge as a mixed-integer nonlinear programming problem. The C-SMTL plays a pivotal role in learning, collaborating, and adapting transmission power and interference coordination strategies over time. Simulation results underscore H-RAN's capability to manage these conflicting objectives effectively, demonstrating significant network performance improvements. Future research will concentrate on dynamic frequency-switching strategies.

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