AI-driven Integration of Sensing and Communication in the 6G Era

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***Abstract*—Attributing to the rapid growth of AI, the integration of sensing and communication (ISAC) networks has embraced AI in the upcoming new-style mobile communication networks. A FedFog network architecture for ISAC networks is proposed in this article, which consists of the terminal perception layer, the edge base station processing layer, and the cloud data layer. In the context of multiple base stations (BSs), the handover between BSs and user equipment is worthy to be studied. Referring to the concept of coordinated multiples BSs, we design a handover procedures in the ISAC networks. Meanwhile, a federated reinforcement learning scheme of user control is designed. However, due to new unlicensed spectrum bands such as millimeter wave band and Terahertz band, the hybrid beamforming can reduce the expenses of hardware. A learning-based interference management utilizing the hybrid beamforming is designed. Meanwhile, we consider self-interference and mutual interference cancellation with deep neural networks. Simulation results show the performance of AI-driven ISAC networks in terms of mobility and interference management, and further prove that services are boosted for 6G networks.**

I. Introduction

Nowadays, the hotspot coverage and its signals are scattered in all corners to satisfy the work and entertainment needs on a daily basis. There are now more than 9 billion terminals covering the globe [1]. People's living grows to be intimately attached to sensing signals. The internet of things (IoT) is also constantly striving to obtain ubiquitous connectivity, and the use of radar echoes to support the IoT under ubiquitous connectivity is also a trend in the prospective field. With the advent of mobile communication networks, human beings can enjoy a higher transmission rate and lower latency than before. Broad IoT scenarios, high definition, fast transmission, and dense high-capacity network environments all place high demands on the next-generation mobile communication networks. The upcoming 6G mobile communication would accommodate a various future IoT needs [2].

In the 6G era, the integration of sensing and communication (ISAC) has been listed as the network paradigm in International Telecommunication Union and 3rd Generation Partnership Project. ISAC networks aim to support the dual functions of radar and communication. To enhance the utilization of the spectrum and reduce the capture of equipment, future ISAC networks require more powerful computing capabilities to process more complicated data. It is in sync with the design target of 6G, integrating intelligence, communication, and perception.

Since the concept of ISAC networks was proposed by Roberton and Brown [3], ISAC networks have gradually been developing. After Orthogonal Frequency Division Multiplexing (OFDM)-supported ISAC networks were designed [4], the ISAC networks served as a novel network paradigm. It has evolved from functions coexistence, abilities assistance to the final integration three stages [5]. The first stage is functions coexistence, where the antennas and signal process would achieve functions coexistence via shared resources. The sensing subsystem and communication subsystem are isolated. And in the stage of abilities assistance, sensing-aided communication and communication-aided sensing would be obtained to promote communication and sensing together. The final integration stage is set at the full integration of physical hardware, protocol, and AI-assistance integration. It can obtain the native sensing and intelligent IoT in 6G era.

To obtain the full integration stage, especially for the AI-assistance integration. edge intelligence and ISAC are interdependent. On the one hand, a large amount of data would be generated in distributed wireless transceivers. These data requires AI algorithms to process properly and satisfy the ultra-low-delay control needs [4]. On the other hand, edge intelligence consists of sensing, communication, training, and inference. The first two phases requires the assistance of ISAC.

The design of the AI-driven ISAC networks attracts extensive focuses [6]–[8]. Through edge intelligence, a trained model can be deployed and its inference abilities can make decisions. Edge intelligence can be divided into two types: distributed learning and centralized learning [6]. As one of distributed learning techniques, the federated learning is more applicable to the local computing available. Liu et al. designed vertical federated learning to obtain collaborative recognition [7]. Meanwhile, task-oriented integrated sensing, communication, and computing networks are proposed in [8], which is a trail of edge intelligence and ISAC networks. How to design an AI-driven network architecture is considered and studied further.

However, the AI-driven ISAC networks faced with many technical challenges. Firstly, the pressure of communication links would be increased, caused by the sink of AI model. Edge intelligence would enable UE the ability of processing

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data and interact with the base stations (BSs) and cloud process center. How to process the amount of data is of significance. Secondly, the training cost of AI model is not suitable for the ultra-low-delay requirement. Edge intelligence can make a difference in the stage of inference [9]. In the training stage, edge intelligence deal with ultra-low-delay task is intractable. Thirdly, the privacy of data is difficult to protect when the AI model sink into the terminals. How to obtain edge intelligence in ISAC network is an essential issue, without damaging of the user data privacy.

Currently, the studies on AI-driven ISAC network architecture are proceeding. Liu et al. proposed the network-level ISAC, cloud radio access networks (C-RAN) [4], utilizing the powerful cloud computing capacities to process the massive data from the sensing layer. On the basis of C-RAN, Yan et al. noted the cloud-edge collaborative architecture to serve equipment in access networks [8]. The ISAC user equipment (UE) deploys the central unit and distributed unit separately. The remote radio heads (RRHs) are equipped with the function of radio and some physical functions, which can process data locally. The advancement of edge intelligence enables sensing data to be mined further and federated learning to be applied. Federated learning is a promising technique which can process non-independent and identically distributed (non-idd) data from mobile communication environment. Meanwhile, the privacy and security can be guaranteed with with secure multiparty computation and differential privacy. Utilizing federated learning, this distributed machine learning can deploy AI model efficiently. It can further reduce transmission delay, contributing to the expansion of all AI algorithms.

In the fast-speed-mobility scenario, such as automatic drive and drone inspection, ISAC UE's moving would cause frequent handover access. Mobility management is worth studying and designing [10]. However, studies on mobility management in ISAC networks are scarce. Traditional mobility management barely fits with ISAC networks. Meanwhile, mainstream theories considering access control does not involve edge intelligence. Edge intelligence is commonly absent in mainstream theories regarding access control. It leads to the waste of computing resource. Practically, given the presence of interference and noises, UE serves to distinguish radar echoes from communication signals. Machine learning to mine data features facilitates tackling the challenge.

Massive multiple-input multiple-output (MIMO) is a pivotal technology to current and future ISAC networks, and henceforth it is necessary to design their corresponding beamforming for the gain of these antennas efficiently [11]. On the one hand, the communication function prior to the design of the narrow beamforming, achieves spatial multiplexing conveniently. On the other hand, sensing calls for broader beam width to capture more information from reflectors. Due to the full-duplex mode, the interference exists inevitably. Beside extensive mutual interference, the self-interference is not ignored. The two types of interference generate challenges in designing the beamforming of ISAC networks. Machine learning can reduce the complexity of beamforming. The online learning model can generate beamforming patterns and codebooks. To some extent, the trained beamforming can offset the power of mutual interference. Additionally, the nonlinear part of self-interference can be approximated by the deep neural networks, which is accomplished in traditional full-duplex wireless communications.

In this article, we first present an AI-driven ISAC network architecture in line with the requirements in the 6G era. Under the established network architecture, a sensing-aided handover procedure is born to adjust the state-of-the-art ISAC networks. User control utilizing federated reinforcement learning is taken into consideration as well. Subsequently, we present the hybrid beamforming together with its corresponding mutual interference management method, followed by the deep neural networks to cancel self-interference in ISAC networks.

II. Network Architecture

As shown in Fig. 1, we consider an AI-driven ISAC network architecture equipped with multiple BSs. These BSs take advantage of limited resources such as frequency, time, and space. Although there has been extensive and in-depth research on the ISAC networks, the current ISAC networks do not integrate into strong supportive computing capacity. So it is necessary to combine distributed edge computing and AI to build an intelligent ISAC distributed network architecture for 6G. The AI-driven ISAC distributed network architecture has three main layers: The terminal perception layer, the edge base station processing layer, and the cloud data center layer. The interaction pattern between the terminal perception layer and edge base station processing layer is federated learning architecture, while the edge base station processing layer and the cloud data center layer are implemented through the edge computing. The terminal perception layer involves a variety of perception detection equipment that will produce a tremendous amount of data, if each UE equips with a deep neural network. Adopting the featured data instead of raw data can effectively alleviate the pressure from communication link between the BS and each UE. Federated learning trains iteratively, utilizing the interact between the local learning model and the global model. Subsequently, the fog BS then downloads the global model parameters from the cloud-data center. And the final training model updates with good performance.

Firstly, each UE will occupy individual data distribution due to its environment information. The particular benefits of different UEs pursues while substantial chunks of row data are transmitted difficultly. The federated learning can aid each UE in processing its row data locally. The featured data is uploaded to BSs. Concurrently, employing the federated learning, each UE can obtain the machine learning in the terminal perception layer to establish massive parallel machine learning.

Configured with computing resources, storage resources, and a global neural network, the edge base station processing layer processes the characteristic data of these sensing probe devices. It also has a fronthaul link to interact with the baseband unit (BBU) pool of the cloud data center layer. The structure of the fog wireless access network establishes, as shown in Fig. 1, specifically a BBU, a high power node, wireless RRHs, and BSs. Among them, the wireless remote

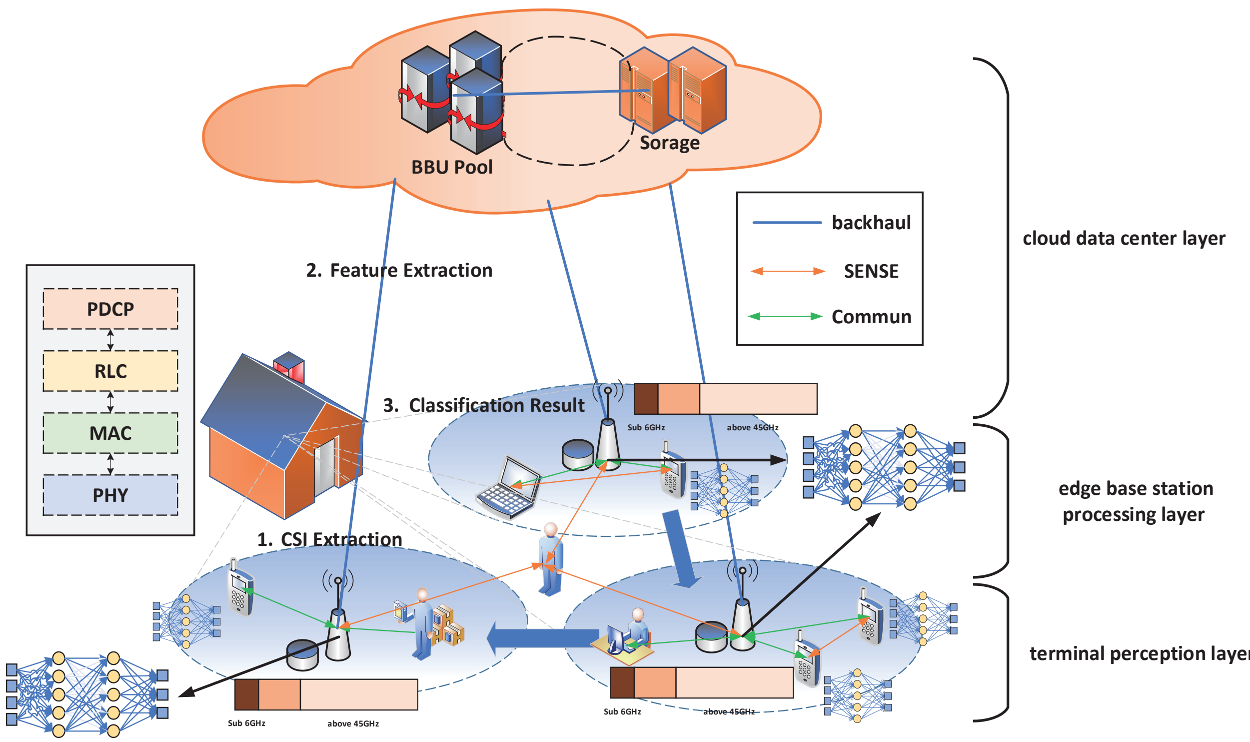

Fig. 1. The AI-driven ISAC network architecture.

radio unit connects to the BBU pool via the fronthaul link to achieve centralized communication, caching and computing functions. F-BSs have wireless signal processing capabilities, edge caching, computing, and AI capabilities. The high-power nodes connect to the BBU pool through a backhaul link to implement the control layer function of the network. In addition, through this architecture, AI algorithms are deployed in the BBU pool (cloud data center layer), BS (edge base station processing layer), and UE (terminal perception layer) to increase the ability of network adaptation and service awareness adaptation, and facilitate the dynamic collaboration of multi-dimensional resources in the network. Particularly, UEs lower overhead backhaul/fronthaul data transmission to meet commercial and performance requirements.

III. Mobility Management in AI-driven ISAC Networks

For the sensing function in ISAC networks, the handover is not limited from one UE to another. The issue on handover is not novel but necessary in traditional wireless networks. However, due to the integration of sensing functions, the handover in ISAC networks is not different from before. On the one hand, the time alignment of sensing results in synchronization. The rapid shift of targets strengthens the difficulties of beam tracking. On the other hand, the matrices like azimuth angles (Angle-of-Arrival/Angle-of-Departure) and sensing precision on ISAC networks are added.

The FedFog network architecture aids mobility management to deal with these difficulties. Initially, the handover on FedFog network architecture is trailed. Subsequently, we propose the user control with federated reinforcement learning on the basis of the designed network architecture.

A. Handover Procedure between Different BSs

Seamless mobility is one of decisive qualities in ISAC networks. During the handover process, there should be no package loss or radio link failure to ensure the UE's quality of service (QoS). Apparently, the sensing-aided procedure is not explored in the current studies on ISAC networks. Therefore, studying the handover between different BSs is necessary. Because of each BS's limited coverage of hot area, it may need to switch to the associated BS when a UE moves in different cells.

Fig. 2 shows the handover procedure and signaling flow for the handover from a UE to a BS in the proposed AI-driven ISAC networks. This is fundamentally based on the coordinated multi-point in heterogeneous C-RANs. Besides, the sensing function between different BSs is leveraged. Meanwhile, it can serve for the UE's handover procedure. This procedure proceeds as follows. Firstly, UEs exchange information within each other using their native sensing capability. Secondly, sensing measurements perform by request and setup transmissions. Then a sensing session is started by a UE as an initiator. Finally, UEs can exchange sensing feedback and information.

There are four steps for the federated learning. Firstly, each UE updates its gradient. Subsequently, updated parameters is globally aggregated in the BS server. And then, global training updates in the BS server. Finally, the global model is downloaded and transformed to UEs. After obtaining channel state

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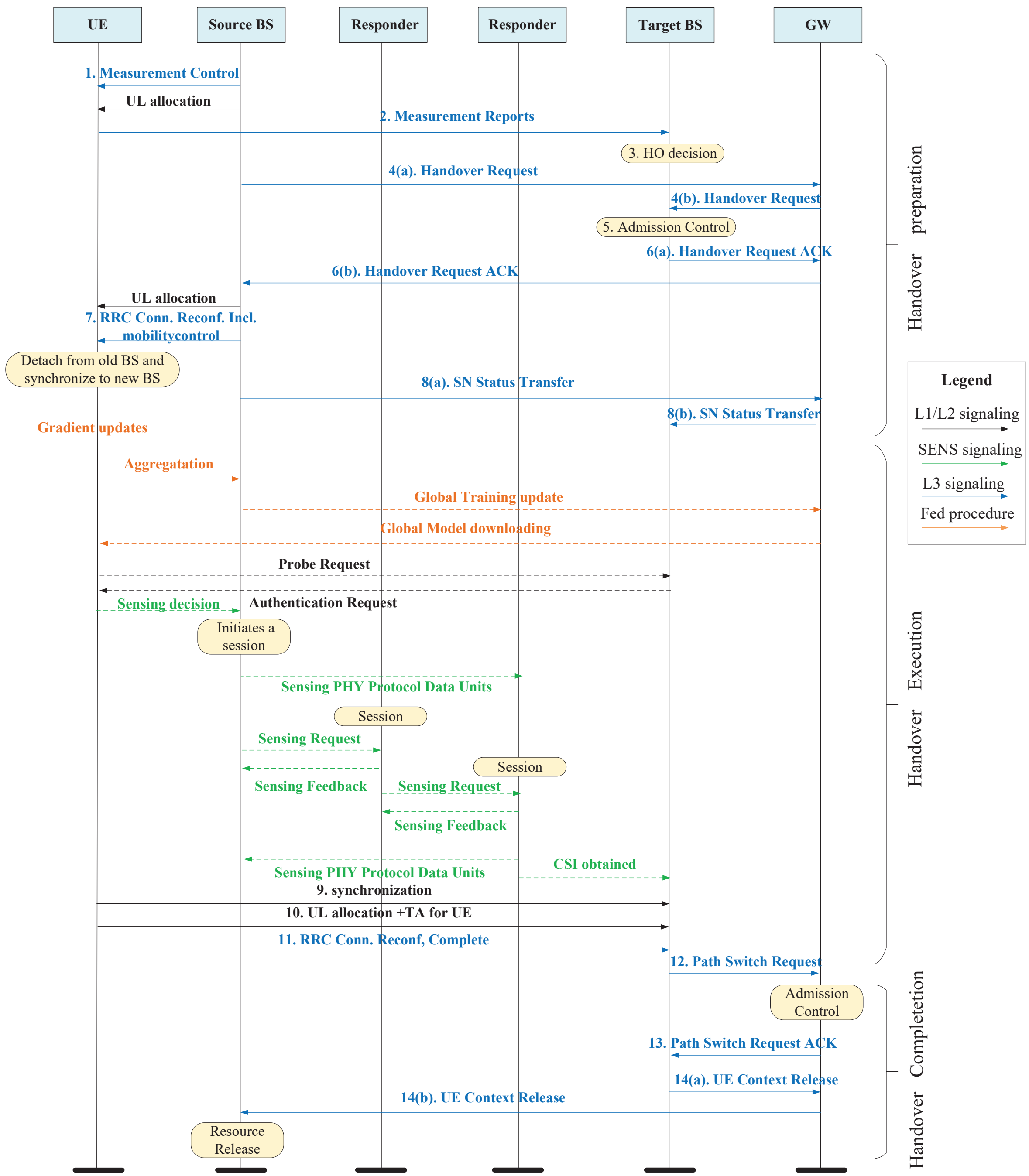

Fig. 2. The handover procedures in the AI-driven ISAC networks.

information (CSI) through sensing operations, the UE detects the possible set of the next BS based on the CSI measured by the sensing operation. The UE chooses its nearby BSs as the destination BS. The association of the UE and the BS is achievable through the four-way handshake. Fig. 2 presents the handover procedure of a UE from one BS to another BS in the AI-driven ISAC networks. It is mainly referred to as the handover management in fog radio access networks, whilst the initial framework does not consider sensing (SENS in Fig. 2). Source BS transmits a handover request to the target BS. Afterwards, the handover request acknowledges character (ACK) is transmitted to source BS. After SENS operation, the synchronization, uplink allocation, and the radio resource control (RRC) signal are completed. And thereby, the resource release is obtained by path switch and UE context release.

To illustrate the convenience raised by this sensing-aided handover management, we have make simulation results in Fig. 3. Similar to the mobility management in LTE and IEEE 802.11 ax, the signaling overhead of handover can be expressed in terms of transmission time and process time. Fig. 3 shows the signaling overhead of handover with the average session arrival rate λ increasing. The reason why this tendency

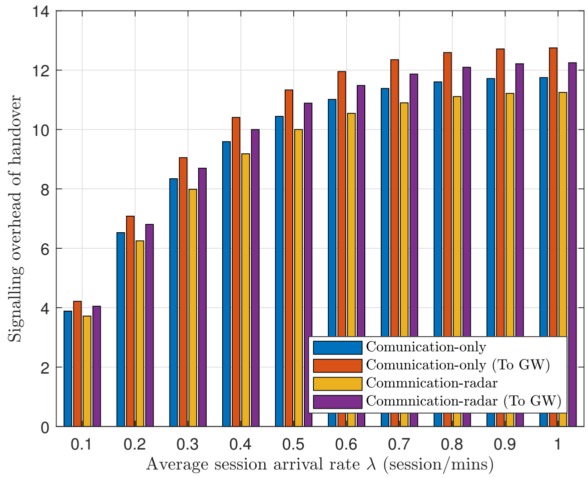

Fig. 3. The handover procedures in the AI-driven ISAC networks.

occurs is that more handovers occur as the average session arrival rate λ increases. The signaling overhead is the product of the probability of handover and the cost, including transmission cost and processing cost. Thus, the signaling overhead of handover is then increasing. As the average session arrival rate λ increases, the overhead also increases. Compared with communication-only scenario, communication-radar scenario equipped with sensing session, the overhead can be saved to some extent. Therefore, the handover procedure in AI-driven ISAC networks can result in a significant reduction in signaling overhead than in conventional Wi-Fi networks.

B. User Access Control in AI-driven ISAC networks

In the substantial deployment of ISAC networks, each UE is supposed to be associated with a suitable BS, to maximize the total throughput, namely access control. The decision of access control is made by some matrices, such as the received signal strength or capacity. Higher received signal strength indicates better communication conditions, which can lead to higher data rates and more stable connections. Besides, capacity represents the ratio between the amount of data actually transmitted in the wireless channel and the available bandwidth. By optimizing access control policies, bandwidth utilization can be improved, enabling the system to support multiple UEs more efficiently. According to these matrices, the UE would access the BS that occupies the highest RSS or capacity. Subsequently, this scheme would cause frequent handover and offloading equalization. In the future ISAC networks, the matrices would range from the conventional communication matrices to the radar echo matrices. The user control scheme of federated reinforcement learning is designed in such context. The binary index indicates the user association in the time slot. If the UE is associated with the BS, the binary index equals 1. Otherwise, the binary index equals 0. Each UE is equipped with individual deep neural networks. And the UE's state space consists of the user access factor and the channel state. The action space includes the $\mathbf{s}_k\left(t\right) \triangleq \left\{\mathbf{x}_k\left(t-1\right); \mathbf{h}_k\left(t-1\right); \omega_k\left(t-1\right)\right\}$ and $\mathbf{a}_i\left(t\right) \triangleq \left\{\mathbf{x}_k\left(t\right)\right\}$, respectively. The reward function is set as the weighted sum of the communication matric and the sensing matric. Through the deep reinforcement learning architecture, a loss function can be obtained by the time difference of each batch. After collecting each UE's loss function, the local feature model requires transmission. It is referred to as the concept of federated learning and consists of two stages, the selection of UE and global model aggregation. The first stage is significant for its impact on the performance of federated learning. The objective of federated learning is to minimize the ergodic global loss function, and it can transform into a minimization of the ergodic loss function. After the appropriate UE is selected, the global model is aggregated, utilizing common FedSGD and FedAvg. Finally, the global feature parameters $\omega_{global,j}\left(t\right)$ are updated by the local feature parameters $\omega_k\left(t\right)$.

In addition to access control factors, power control factors and bandwidth allocated factors are also incorporated into AI-driven ISAC networks. As to discrete access control factors, such common deep reinforcement learning as deep Q-networks (DQN), Dueling DQN, and Double DQN, can be utilized to optimize. Moreover, continuous power control factor and bandwidth allocated factor would be obtained by deep deterministic policy gradient, proximal policy optimization, asynchronous advantage actor-critic, etc.

IV. Learning-based interference management in AI-driven Integration of Sensing and Communications

At present, the unlicensed spectrum includes 1-7.125 GHz and above-45 GHz frequency bands, which supports sensing. With respect of above-45 GHz frequency bands, the hybrid beamforming is utilized, unlike sub-6 GHz frequency band. The practical challenges and limitations mainly derive from the following two aspects. Due to the higher frequency, the signal is more easily blocked and attenuated by objects during propagation, resulting in shorter transmission distances. Additionally, terahertz and mmWave bands have short wavelengths, and effective communication requires properly designed antennas and beamforming techniques. To address the first challenge, it requires efficient handover and access control to maintain reliable communications. The transmission distances under these spectrum band are short, so the frequent handover is inevitable. The mobility management has been discussed in the last section. As for the design of beamforming techinique, intelligent sensing and management of spectrum can be achieved. AI can help optimize the allocation and utilization of spectrum resources, predict and adapt to spectrum demands under different applications and network settings, and improve spectrum utilization efficiency and performance.

Beamforming in ISAC networks is a research focus on 6G networked sensing [11] because the above-45 GHz frequency band (e.g. millimeter Wave or Terahertz) requires a high number of antennas [12]. It does not accommodate the massive MIMO in the new-style wireless communication networks. Hybrid beamforming enables the overhead of hardware to be far alleviated [13]. The received signal after hybrid beamforming is attainable by the Saleh-Valenzuela channel model.

Spectral efficiency is realizable with the help of the Shannon formula. Meanwhile, the detecting precision of different targets' angle-of-departures can be measured by mean-square-error (MSE). If the MSE is transformed into a constraint and regards spectral efficiency as the utility function, the hybrid beamforming in ISAC networks becomes a communication-centric optimization problem. If the objective function is to minimize the MSE, this problem is an issue of sensing-centric optimization.

We consider a simulation scenario in which 40 single-antenna UEs are uniformly distributed within the floor (0.1 m of minimum inter UE distance) and located at 1 m height. 3GPP TR38.901 InH with mixed office line of sight probability. Internal wall losses are considered statistically. A 40×40 m^2 indoor sensing scenario is considered. 4 BSs are randomly deployed in the coverage of benchmarks, including (10, 10), (10, 30), (30, 10), and (30, 30), individually. After scattering each BS's location, each BS's UE is deployed its coverage randomly. The radius of benchmarks is set as 10 m, and the BS's radius is set as 10 m.

TABLE I
DETAILED SIMULATION PARAMETERS.

Parameter	Value
Carrier frequency	60 GHz
Bandwidth	80 MHz
BS TX power	1 W
Thermal noise	-174 dBm/Hz
The number of BSs	4
The number of BS TXs	10 - 40
BS Density	0.025 m^{-2}
UE Density	0.25 m^{-2}
BS digital precoding	Zero forcing
Pathloss	3GPP TR38.901 InH (Release 16)
UE association	Based on RSRP
Multiple access scheme	OFDMA

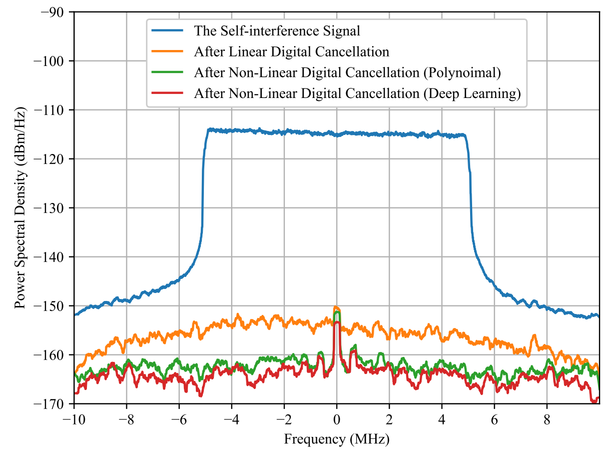

Fig. 4. Power spectral densities of the self-interference signal.

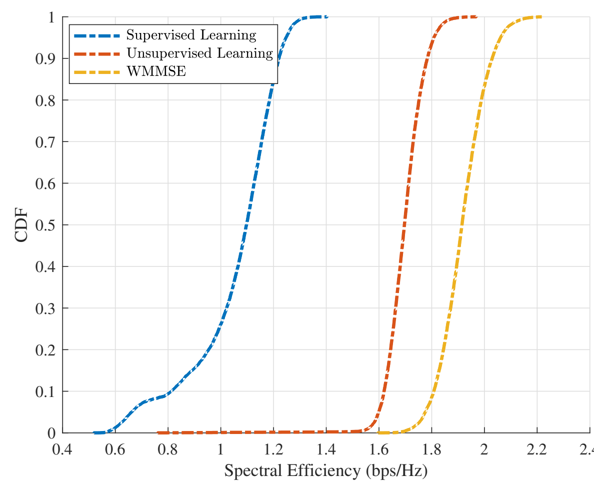

Fig. 5. The cumulative distribution functions (CDFs) of spectral efficiency.

Owing to the full-duplex feature of ISAC signal, the interference is generated from alternate BSs between the communication system and the sensing system. Interference covers self-interference and mutual interference. Affected by its receiver, the transmitted signal generates self-interference from the UE's transmitter. Aside from self-interference, the shared spectrum leads to the mutual interference between different communication signals and radar echoes. When the echo signal of the radar system interferes with the communication signal, it leads to a decrease in radar performance, such as the accuracy of target detection and resolve distances. This requires coordination and interference management strategies between radar and communication systems, such as time-division multiplexing, frequency planning, and signal processing techniques.

The detailed parameters used in the simulation can be found in Table 1.

The deep learning technique deserves trying, especially in more intricate interference settings [14]. Due to its universal approximation principle, the deep learning can optimize the beamforming dynamically with no interference. Whether self-interference or mutual interference, the deep learning is applicable for inference. Meanwhile, the deep learning technique is suitable for the FedFog network architecture.

Linear distortion in self-jamming signals is available by linear elimination, but there is no suitable elimination method for nonlinear distortion parts, whereas deep neural networks are capable of approximating complex self-interference models, especially for nonlinear ones. The target of deep neural networks is to predict the non-linear part $\widehat{y}_{nl}$, based on the data set (x, y_{nl}). As shown in Fig. 4, self-interference cancellation is presented. It is obvious that digital linear cancellation can obtain approximately 40 dB cancellation. Furthermore, the deep learning non-linear cancellation can obtain 8 dB cancellation, which is next to the received noise. To verify the effectiveness of deep learning method, we added the polynoimal method. It can be seen these two method obtain the nearly unanimous cancellation performance.

Furthermore, the existing work on deep learning, chiefly dependent on the elaborate training set, are not flexible and convenient. Supervised learning requires a large amount of labeled data for training. This labeled data requires manual labeling, expert knowledge and time commitment. For some domains or tasks, acquiring large-scale labeled data can be difficult and expensive.

The unsupervised learning method gradually earns recognition and attention from the academics [15]. Fig. 5 compares different beamforming methods on their spectral efficiency, and the spectral efficiency reveals the performance of interference management. Besides, we also listed the supervised learning method and the the weighted minimum-mean-square-error (WMMSE) method. The WMMSE method is a conventional one to locate the optimal solution for beamforming. The supervised learning method derives from the training set raised by the WMMSE method. The unsupervised learning method and supervised learning method are in the same conditions. The optimizer is set as Adam and the learning rate is set as 1×10^{-3}. Both of the methods utilize three-layer deep neural networks. Concerning the parameters, the initial weights are generated by the uniform distribution, and initial bias values are set as 0.1. The first layer is 20. The second layer is 30. The third layer is 20. Noticeably, the unsupervised learning method performs better spectra efficiency than the supervised learning one. In conclusion, the unsupervised learning method is more flexible in the interference management in the ISAC networks.

V. Conclusion and Future Work

This article elaborates AI-driven ISAC networks in the upcoming 6G era. The FedFog network architecture leverages the CSI to aid sensing and communication. In the context of CoMP in upcoming 6G networks, this article proposes an innovative handover procedure by utilizing the sensing session. On the basis of the hybrid beamforming, we design a learning-based method to manage self-interference and mutual interference in the AI-driven ISAC networks.

What we have discussed in this article is the part of the theoretical foundation for AI-driven ISAC networks. There remain considerable challenges and open issues to be overcome in the further work. 1) The collection and process of multi-modal data in ISAC networks. Faced with fruitful data from different conditions, such as frequency band, waveform, and coding, the collected data is complicated. Accordingly, data modalities vary with the influence of different spatio-temporal situations and UE types. 2) The choice of supervised learning method or unsupervised learning method. The featured data sets require enough time and scales to construct. The scales of provided data vary from scenario to scenario. supervised learning method and unsupervised learning method have their strengths and drawbacks. 3) The incorporation of mobile edge computing into the proposed network architecture. The tendency for communication-sensing-computing incorporation in future wireless networks is emerging robustly. The AI-driven ISAC networks are prospective to exploit the joint effort of native functions and mobile edge computing.

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