FedISAC: A Federated Learning Framework with Integrated Sensing and Communication for 6G mmWave Networks

Apurba Adhikary[1], Girum Fitihamlak Ejigu[1], Kitae Kim[1], Min Kyu Suh[2], and Choong Seon Hong[1]*
[1]Dept. of CSE, [2]Dept. of AI, Kyung Hee University, Yongin-si 17104, Republic of Korea
E-mail: {apurba, girumfitex, glideslope, minkyu0226, cshong}@khu.ac.kr

***Abstract*—The 6G communication networks are designed to provide secure communication, higher data throughput, minimized power consumption, improved system performance, and enhanced device integration, paving the way for more intelligent and efficient networking systems. To achieve these goals, an AI framework is proposed that integrates the integrated sensing and communication (ISAC) with the federated learning (FL) scheme, where local devices send their sensing information to the global base station (GBS) after local training. The GBS then aggregates this local sensing information and allocates the desired aggregated average power to the local devices based on the aggregated sensing information of the local devices. An optimization problem is formulated to minimize the global model loss, ensure desired power allocation, and maintain improved signal-to-interference-plus-noise ratio (SINR) and achievable rate (AR). An AI framework is proposed, utilizing a federated averaging (FedAvg) algorithm to address the formulated problem and allocate the necessary power to local devices based on their sensing information. Simulation results reveal that our FedAvg-based AI framework achieves cumulative SINR improvements of 1.02 dB, 1.01 dB, and 1.01 dB, and AR enhancements of 1.71 bps/Hz, 1.70 bps/Hz, and 1.70 bps/Hz, outperforming federated proximal, centralized training, and average local training methods, respectively.**

***Index Terms*—Integrated sensing and communication, federated learning, federated averaging, power allocation, mmWave.**

I. Introduction

The rapid proliferation of mobile devices and diverse applications has introduced new user demands, driving the development of 6G communication networks to deliver secured communication, higher data throughput, lower power consumption, improved system performance, and enhanced device integration, paving the way for more intelligent and efficient networking systems [1]–[5]. Integrated sensing and communication (ISAC) aim to integrate communication and sensing capabilities on a unified platform, enabling the shared use of signal-processing resources and wireless infrastructure for both software and hardware, which enhances network performance by improving power savings, achievable rate (AR), signal-to-interference-plus-noise ratio (SINR), and hardware utilization [6]. However, privacy and security concerns are associated with artificial intelligence (AI) due to the inherently sensitive nature of the information of the applications. To address these challenges, federated learning (FL) offers a promising solution by enabling distributed training of neural network models and facilitates collaboration between local devices and a global base station (GBS) while ensuring the secrecy of sensitive data [7], [8]. Therefore, integrating federated learning with ISAC (FedISAC) for the millimeter-wave (mmWave) networks can improve the system's performance with secured communication, power savings, SINR, and AR.

Several studies have analyzed the challenges of leveraging ISAC in intelligent omni-surface (IOS) or reconfigurable holographic surface-based cell-free (CF) networks and holographic MIMO (HMIMO)-based systems. In [9], the authors proposed a holographic ISAC system utilizing amplitude-controlled metasurface antennas to address spectrum congestion issues. The authors in [6] propose integrating HMIMO BSs into CF networks, replacing traditional BSs with HMIMO BSs to secure an energy-efficient, HMIMO-empowered CF network for 6G systems leveraging ISAC. The work in [10] proposes an AI-based framework leveraging ISAC, coexisting with HMIMO BSs and IOS, to enhance wireless coverage and reduce power consumption. In [11], an ISAC-based AI framework is proposed to ensure reduced power usage by selecting the fewest possible grids from the holographic array to deliver efficient beamforming for serving users. However, no studies have considered integrating the ISAC scheme with the FL framework, where local sensing information is sent from the local devices to the GBS, which then allocates the aggregated average power back to the local devices. The core contributions are outlined as follows:

- We propose an AI framework that integrates the ISAC scheme with the FL framework, where local devices send the sensing information to the GBS after local training at the local devices.
- The GBS then allocates the aggregated average power back to the local devices based on the aggregated sensing information of the local devices.
- We formulate an optimization problem that minimizes the global model loss, ensuring desired power allocation while maintaining improved SINR and AR.
- We design an AI framework that employs a federated averaging (FedAvg) algorithm to address the formulated problem and allocate the required power to local devices based on their sensing information.
- Simulation results show that our proposed FedAvg-based AI framework achieves cumulative improvements of 1.02 dB, 1.01 dB, and 1.01 dB in SINR, and 1.71 bps/Hz, 1.70 bps/Hz, and 1.70 bps/Hz in AR, compared to federated

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proximal (FedProx), centralized training, and average local training methods, respectively.

II. System Model

We propose a system model to enable a federated learning framework with integrated sensing and communication that ensures a decentralized approach for collaborative learning in wireless networks leveraging ISAC capabilities, as demonstrated in Fig. 1. The proposed FedISAC system model considers a GBS and a set of local devices $\mathcal{U} = \{1, \ldots, u, \ldots, U\}$, which together facilitate collaborative model training without the need for direct data sharing among the local devices. Each local device is equipped with a local dataset, which is used to train a local machine-learning model and the dataset contains features related to the ISAC. The local devices preprocess the required data by normalizing the features and applying log scaling, ensuring that the models are trained on standardized data. The local model integrated into each local device is a neural network with three fully connected layers, the first two layers serve as feature extractors and use ReLU activation functions to introduce non-linearity, while the final layer outputs the required power allocation. The local model is trained using the dataset of the local devices to minimize the error between the allocated and original power values.

The GBS functions as the orchestrator of the FedISAC process. Each local device transmits its sensing information (i.e., distances, azimuth angles, and zenith angles) and locally trained model parameters (i.e., biases and weights) to the GBS after a desired number of local training iterations, which is regarded as the sensing process of the ISAC scheme. The GBS aggregates the sensing information considering the locally trained model parameters by averaging them, to update a global model that captures the collective knowledge of all local devices. The GBS allocates the necessary power to each local device based on the aggregated sensing information and the global model, which serves as the basis for the next phase of local training. This process is considered the communication process of the ISAC scheme. The primary task of the local devices is to perform local computations for model training and send the sensing information to GBS. On the contrary, the GBS allocates the required aggregated power to the local devices by analyzing the aggregated sensing information of the local devices. Consequently, the FedISAC system ensures better performance in power allocation, improves the accuracy of trained models by leveraging sensing information, and enhances communication performance. The proposed FedISAC system involves the following six steps:

1) Step 1: The initialized global sensing information is sent to local devices.
2) Step 2: Training is carried out leveraging local datasets on local devices that are associated with the local model.
3) Step 3: The local sensing information is sent to GBS after a necessary number of local training iterations.
4) Step 4: The GBS aggregates the sensing information for power allocation to local devices.

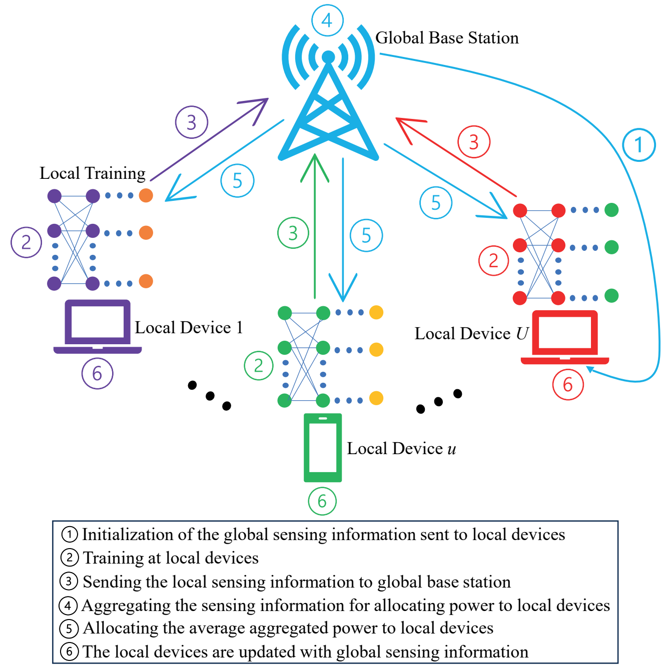

Fig. 1. A System model for FL framework with ISAC scheme.

5) Step 5: The GBS allocates the average aggregated power to local devices based on the aggregated sensing information of the local devices.
6) Step 6: The local devices are updated with global sensing information, which acts as the foundation for the subsequent round of local training.

A. Sensing Model

The FedISAC system is a distributed approach to machine learning, where multiple local datasets are trained independently, and model updates are shared with a GBS, which is useful to ensure data privacy and security in wireless communication networks for effective power allocation based on the sensing information of the local devices. The GBS aggregates the updates to form a global model, which is then redistributed to the local devices for further training. The use of neural networks for power allocation of the local devices, combined with a federated learning approach, ensures more efficient power management, reducing overall energy consumption and enhancing the performance of the communication network. Each local device u has its local dataset D_u and trains a local model $\boldsymbol{w}_u$ using its data. The sensing information s_u of each local device u is used to adjust the local model for E epochs of training before updating is represented as [7]

$$\boldsymbol{w}_u^{(t+1)} = \boldsymbol{w}_u^{(t)} - \eta \nabla \mathcal{L}_u(\boldsymbol{w}_u^{(t)}, \mathcal{D}_u, \mathbf{s}_u), \tag{1}$$

where $\boldsymbol{w}_u^{(t)}$ is the local model weights at local device u in round t, s_u is the sensing information that influences the model update, η is the learning rate, and $\nabla \mathcal{L}_u(\boldsymbol{w}_u^{(t)}, \mathcal{D}_u, \mathbf{s}_u)$ represents the gradient of the loss function $\mathcal{L}$ computed using the local dataset $\mathcal{D}_u$ for obtaining the sensing information. The sensing information of the local devices such as distances, zenith angles and azimuth angles of the local devices are sent to the GBS. It is assumed that $\boldsymbol{Z}_u$ and $\boldsymbol{A}_u$ represents the zenith and azimuth angles, respectively, where $(\boldsymbol{Z}_u, \boldsymbol{A}_u) \in [0, 2\pi)$.

B. Communication Model

The GBS combines the local models to produce an updated global model $\boldsymbol{w}^{(t+1)}$, which is achieved with the weighted average based on the size of the local datasets and sensing information of the local devices. The local devices with larger datasets have a more significant impact on the updated global model. The updated global model $\boldsymbol{w}^{(t+1)}$ is redistributed to all local devices for the next round of training, and the iterative process continues for multiple rounds until convergence is achieved. This iterative training and aggregation process allows the global model to progressively improve its performance on the power allocation task, benefiting from the diverse data distribution of all local devices without centralizing any data. The overall loss function for the global model after aggregation is represented as [12]

$$\mathcal{L}(w) = \sum_{u=1}^{U} \frac{n_u}{n} \mathcal{L}_u(w, \mathcal{D}_u), \tag{2}$$

where U is the total number of local devices, n_u is the number of data samples in the local dataset $\mathcal{D}_u$, and n is the total number of samples across all devices, $n = \sum_{u=1}^{U} n_u$. Let us consider that $\boldsymbol{H}_u$ represents the channel between the GBS and local device u and the GBS has M antenna grids. Therefore, the response vectors of the grid array $G_u(Z_u, A_u) \in \mathcal{C}^M$ for the channel of $\boldsymbol{H_u} \in \mathcal{C}^M$ is demonstrated as [13]

$$G_u = [1, e^{j\pi \sin(Z_u)\cos(A_u)} \dots e^{j(M-1)\pi \sin(Z_u)\cos(A_u)}]^T. \tag{3}$$

The GBS allocates the desired power P_u to local device u, which is a function of the sensing information $\boldsymbol{s}_u$ and the global model $w^{(t)}$, as demonstrated by:

$$P_u = f(\mathbf{s}_u, w^{(t)}), \tag{4}$$

where f is a function that combines the sensing information $\boldsymbol{s}_u$ and the global model $w^{(t)}$ to allocate the power $\boldsymbol{P}_u$ to the local device u.

The power allocation of the local devices follows the relationship $\{\boldsymbol{P}_1, \dots, \boldsymbol{P}_u, \dots, \boldsymbol{P}_U\} \in \boldsymbol{P}$ where $\boldsymbol{P}$ is the power allocation matrix of the GBS and the overall transmitted power α at the GBS is represented as $\alpha = \{\boldsymbol{P}\boldsymbol{P}^H\}$. Consequently, the ISAC signal y_u received at local device u is represented as [14]

$$y_u = \boldsymbol{H}_u \boldsymbol{x}_u + \sum_{u' \neq u} \boldsymbol{H}_{u'} \boldsymbol{x}_{u'} + \boldsymbol{\Omega}_u, \tag{5}$$

where $\boldsymbol{x}_u$ is the ISAC transmitted signal from GBS to local device u, $\sum_{u' \neq u} \boldsymbol{H}_{u'} \boldsymbol{x}_{u'}$ is the interference from other local devices, and $\boldsymbol{\Omega}_u$ is the Gaussian noise (CN$(0, \psi^2)$) at local device u. Therefore, the SINR for local device u is expressed as [13]

$$\gamma_u = \frac{\boldsymbol{P}_u \boldsymbol{H}_u \boldsymbol{x}_u}{\sum\limits_{u' \neq u} \boldsymbol{P}_{u'} \boldsymbol{H}_{u'} \boldsymbol{x}_{u'} + \psi^2}, \tag{6}$$

where ψ^2 represents the noise power, and $\boldsymbol{P}_{u'}$ and $\boldsymbol{H}_{u'}$ represent the power and channel for the interfering local device $u^{'}$. Subsequently, the achievable rate (AR) ζ_u for local device u is demonstrated as [13]

$$\zeta_u = \log_2 \left(1 + \frac{\boldsymbol{P}_u \boldsymbol{H}_u \boldsymbol{x}_u}{\sum\limits_{u' \neq u} \boldsymbol{P}_{u'} \boldsymbol{H}_{u'} \boldsymbol{x}_{u'} + \psi^2} \right). \tag{7}$$

III. Problem Formulation

The federated learning model involves multiple local devices U, each with local data D_u. The local devices send sensing information to the GBS, which allocates the desired power $\boldsymbol{P}$ to all local devices based on this information. The core objective is to reduce the global model loss $\mathcal{L}_u(w)$ across all local devices, ensuring more accurate power allocation while maintaining improved SINR and AR. Consequently, we aim to minimize the global loss $\mathcal{L}_u(w)$, which is the weighted sum of local losses from each local device. The weights are proportional to the number of data samples of each local device u. Therefore, the optimization problem is formulated as follows:

$$P1: \min_{\boldsymbol{P}, \boldsymbol{w_u}, \boldsymbol{w}} \sum_{u=1}^{U} \frac{n_u}{n} \mathcal{L}_u(w, \mathcal{D}_u), \tag{8}$$

$$\text{s.t.} \quad \|\boldsymbol{w}_u^{(t+1)} - \boldsymbol{w}^{(t)}\| \leq \delta_u, \forall u \in U, \tag{8a}$$

$$\beta_u \leq \frac{n_u}{n}, \forall u \in U, \tag{8b}$$

$$\gamma_u \leq \xi_m, \forall u \in U, \tag{8c}$$

$$\zeta_u \leq \varrho_m, \forall u \in U, \tag{8d}$$

$$\sum_{u=1}^{U} P_u \leq P_{\mathrm{M}}, \forall u \in U, \tag{8e}$$

$$(\boldsymbol{Z}_u, \boldsymbol{A}_u) \in [0, 2\pi), \forall u \in U. \tag{8f}$$

We consider three decision variables such as $\boldsymbol{P}$, $\boldsymbol{w_u}$, and $\boldsymbol{w}$ in problem (P1) where the local device u sends the sensing information with local model weights $\boldsymbol{w_u}$ to the GBS, which combines the local models to update the global model $\boldsymbol{w}$ and the GBS allocates the required power $\boldsymbol{P_u}$ to local device u from the power allocation matrix $\boldsymbol{P}$ according to the sensing information of the local devices. Constraint (8a) limits the magnitude of the model updates sent by local devices to avoid drastic changes between rounds, where δ_u represents the maximum allowable difference between the local model update at local device u and the previous global model. Constraint (8b) ensures that the data distribution across local devices is balanced and within a certain range to avoid bias during training, where β_u represents the minimum proportion of data that any local device must satisfy to prevent under-representation. Constraints (8c) and (8d) impose the minimum SINR and AR requirements, ξ_m and ϱ_m respectively, for local devices to access the intended services. Constraint (8e) ensures that the total allocated power of all local devices is less than the system's maximum power, P_M. Constraint (8f) imposes a constraint on the zenith angle $\boldsymbol{Z}_u$ and azimuth angle $\boldsymbol{A}_u$, ensuring its range from 0 to 2π for power allocation $\boldsymbol{P}$.

The formulated global model loss minimization problem (P1) is an NP-hard problem due to its non-convexity, data

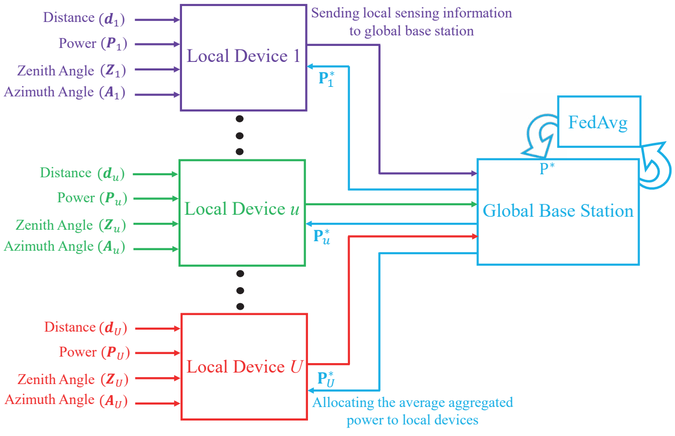

Fig. 2. Overview of AI solution strategies for the FedISAC system, integrating FL with the ISAC scheme.

heterogeneity, power constraints, high-dimensional models, and unpredictable local device participation. Consequently, we employ the FedAvg algorithm to solve the formulated problem (P1) for allocating the necessary power to local devices based on the sensing information, which ensures privacy preservation, efficient power allocation, scalability, and robustness for real-world networking applications. Next, we discuss the details of the FedAvg algorithm.

IV. Federated Averaging Algorithm for ISAC

The FedAvg algorithm is utilized to solve the formulated NP-hard problem (P1), benefiting ISAC systems due to its ability to manage decentralized data, preserve privacy, and ensure efficient communication between local devices and the GBS. FedAvg allows multiple local devices to collaboratively train a machine learning model without sharing their local data, thus safeguarding privacy and minimizing communication overhead. The overall AI solution strategies of the FedISAC system are demonstrated in Fig. 2, where the GBS allocates the desired power to local devices based on the sensing information received from them. For power allocation, sensing information and local model updates are sent to the GBS. The local devices first conduct the training process and send their updates to the GBS, which then uses the FedAvg algorithm to allocate the aggregated average power to the local devices based on model aggregation and the aggregated sensing information.

A. Training Process at Local Device

The local device training process plays an important role in ensuring the effective performance of the FedISAC system, as it involves the optimization of local models based on the individual datasets available at each local device. The training process at the local device is managed using a neural network model that sends the sensing information such as the distances of the local devices, and azimuth and zenith angles to the GBS. Each local device possesses a local dataset that is first normalized to ensure that the features are standardized, which helps in stabilizing the training process. The local model is a neural network with three fully connected layers, where the first two layers extract relevant features from the input

TABLE I

Simulation Parameters

Parameters	Values
Wavelength (λ)	0.0107 m
Sub-band bandwidth	0.05 GHz
Optimizer	Adam
Loss function	MSE
Activation function	Relu
Noise density	-174 dBm/Hz

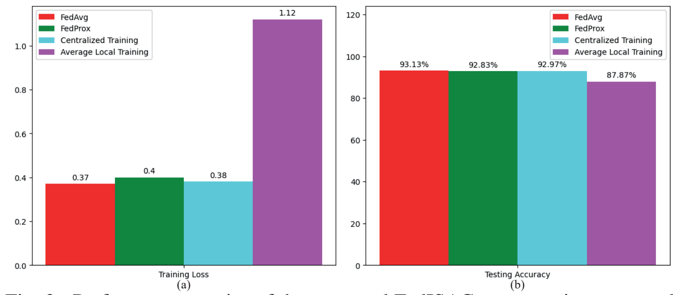

Fig. 3. Performance metrics of the proposed FedISAC system using proposed FedAvg and baseline methods: (a) Training loss; (b) Testing accuracy.

data, while the final layer outputs the required power for allocating to the local devices. The network architecture can be represented as

$$f(x) = W_3 \cdot \text{ReLU}(W_2 \cdot \text{ReLU}(W_1 \cdot x + b_1) + b_2) + b_3, \quad (9)$$

where W_1, W_2, and W_3 and b_1, b_2, and b_3 are the weights and biases of different layers, respectively, and x is the input feature vector. During the training at the local devices, the mean squared error (MSE) is utilized as the loss function that is represented as

$$\mathcal{L}_{u_{\text{MSE}}} = \frac{1}{U} \sum_{i=1}^{U} (z_i - f(x_i))^2, \quad (10)$$

where z_i is the true value and $f(x_i)$ is the predicted value. The model parameters are updated employing gradient descent, where the gradients of the loss function concerning the model parameters are calculated and updated in a way that minimizes the loss. After training on its local dataset, the local device updates its model parameters and sends them to the GBS. The local training ensures that each local device contributes to the global model based on the patterns and characteristics specific to its local data, leading to a more robust and generalized global model. The process continues until convergence is achieved, typically indicated by a reduction in global loss or an improvement in performance metrics.

B. FedAvg at Global Base Station

The FedAvg algorithm serves multiple local devices to collaboratively train a global model under the coordination of the GBS, without directly exchanging their local datasets. The GBS initializes a global model w_0 and broadcasts it to all participating local devices. Each local device u receives the global model w^t at iteration t and uses its local dataset D_k to train the model minimizing the MSE loss function $\mathcal{L}_{u_{\text{MSE}}}$ as expressed in (10). The local model is updated using gradient descent to minimize the MSE loss $\mathcal{L}_{u_{\text{MSE}}}$ according to (1). After a defined number of local iterations, each local device sends its updated model parameters $w_u^{(t+1)}$ to the GBS. The

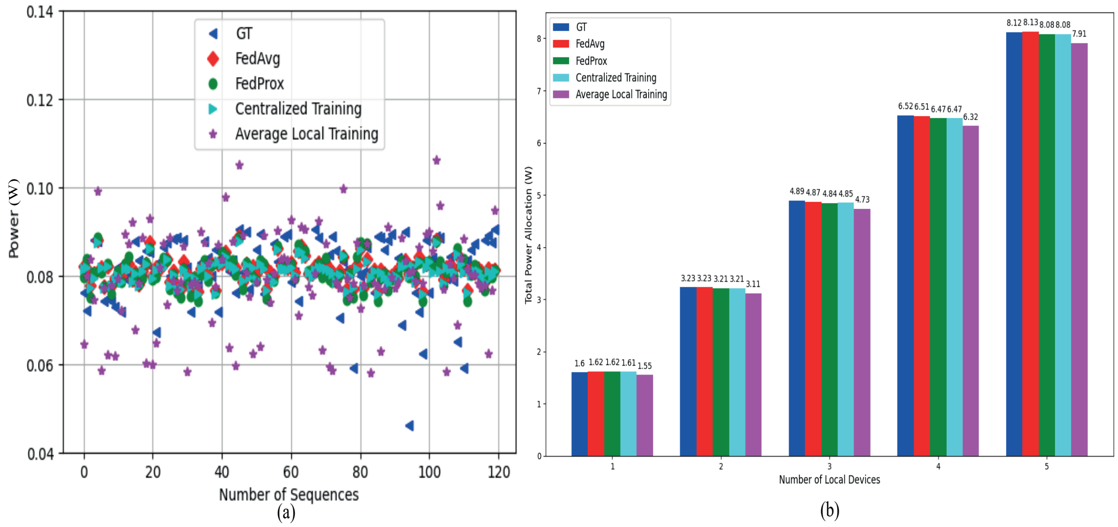

Fig. 4. (a) Total power allocation across different sequences; (b) Comparison of power allocation for 5 local devices using FedAvg and baseline methods.

Algorithm 1 FedAvg Algorithm for ISAC

GBS executes:
Initialize global model parameters $w^{(0)}$ and power $\boldsymbol{P}_u$;
Set number of communication rounds E, number of local epochs E_{local}, and adam optimizer parameters;
for each round $t = 1, 2, \ldots, E$ **do**
  for each local device $u = 1, 2, \ldots, U$ **in parallel do**
    Send global model $w^{(t)}$ to local device u
    $w_u^{(t+1)} \leftarrow$ Update Local Model $(u, w^{(t)})$
  end for
  Aggregate local model updates using (11):
  $w_u^{(t+1)} \leftarrow \frac{1}{U}\sum_{u=1}^{U} \frac{n_u}{n} w_u^{(t+1)}$
end for
Update Local Model $(u, w^{(t)})$ {Run on local device u}
Initialize local model $w \leftarrow w^{(t)}$;
Split local dataset $\mathcal{D}_k$ into mini-batches of size B;
for local epoch $e = 1, 2, \ldots, E_{\text{local}}$ **do**
  for each mini-batch $b \in \mathcal{B}$ **do**
    Compute loss on mini-batch: $\mathcal{L}(w; b)$;
    Compute gradients: $\nabla\mathcal{L}(w; b)$;
    Update local model using adam:
    $w \leftarrow \text{adam}(w, \nabla\mathcal{L}(w; b))$;
  end for
end for
Return updated weights $w_u^{(t+1)}$ to the GBS
Allocate Power: Power $\boldsymbol{P}_u^*$ to serve local device u, $\forall u \in U$.

GBS then aggregates these models to form the updated global model as [12]

$$\boldsymbol{w}^{(t+1)} = \frac{1}{U}\sum_{u=1}^{U} \frac{n_u}{n} \boldsymbol{w}_u^{(t+1)}. \tag{11}$$

The model aggregation ensures that the global model incorporates the knowledge gained by each local device during local training. The updated aggregated global model $w^{(t+1)}$ is then broadcast back to all local devices, and the process repeats until the model converges. Therefore, the FedAvg algorithm effectively balances the contributions of all local devices, leading to a global model that generalizes well across different data distributions while maintaining the privacy of each local device's data. Algorithm 1 demonstrates the overall steps of the FedAvg algorithm leveraging the ISAC process to serve the local devices with the desired power.

V. Performance Evaluation

In this section, we evaluate the performance of the proposed FedISAC system, which ensures a decentralized approach to cooperative learning in wireless networks by leveraging ISAC capabilities and allocating the desired power to local devices based on their sensing information. To evaluate the performance of the FedISAC system, we use the FedAvg algorithm to allocate the required power to five local devices based on their sensing information, employing mmWave technology with an operating frequency of 28 GHz and a maximum power of 10 W and additional simulation parameters are listed in Table I.We prepare our dataset from the DeepMIMO dataset to evaluate the performance of the proposed FedISAC system [15], [16]. We consider the FedProx algorithm, centralized training, and average local training algorithms as baselines for comparison with the proposed FedAvg scheme to demonstrate the effectiveness of the recommended FedISAC framework, taking the ground truth (GT) values into account. Figs. 3(a) and 3(b) show the training loss and testing accuracy for allocating the power to local devices with the proposed FedAvg scheme and other baselines, where the proposed FedAvg scheme outperforms FedProx, centralized training, and average local training, achieving the lowest training loss of 0.37 and the highest accuracy of 93.13% , with a significant margin over the baseline methods. Fig. 4(a) illustrates the power allocation sequences for different local devices, showing that the FedAvg allocation is very close to the GT and outperforms the other baselines by a considerable margin. Conversely, Fig. 4(b) shows the total power allocation for five local devices, where the proposed FedAvg allocates power nearly equal to the GT power for all devices, outperforming the baselines by a notable margin and ensures power savings. However, FedProx and centralized training achieve comparable power allocation to the GT, while average local training results in a larger gap from the GT power and provides the worst performance.

Figs. 5 and 6 represent the achieved SINR and AR for the 5 local devices using FedAvg, FedProx, centralized training, and average local training alongside the obtained SINR and

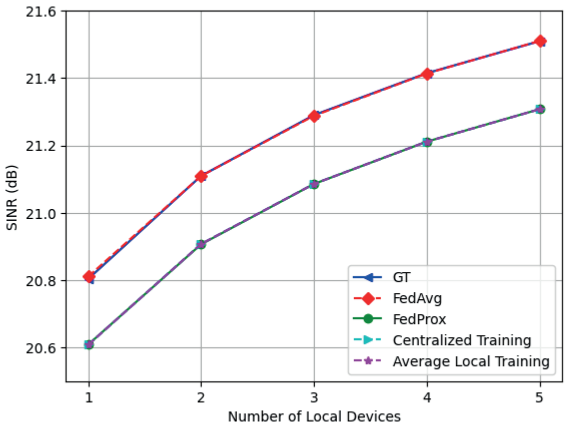

Fig. 5. Comparison of SINR for 5 local devices using FedAvg and baselines.

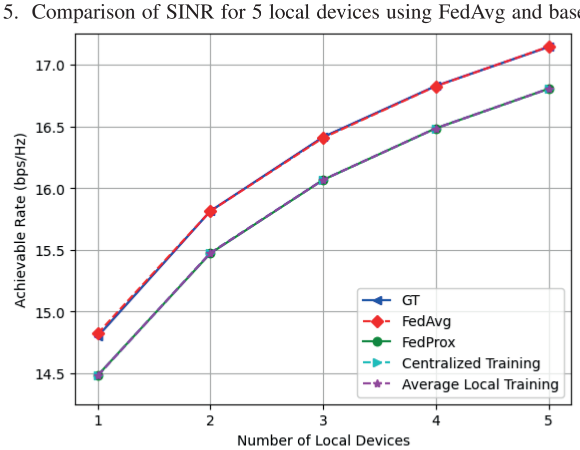

Fig. 6. Comparison of AR for 5 local devices using FedAvg and baselines.

AR with GT, respectively. As shown in Figs. 5 and 6, all the schemes exhibit an increasing trend with the number of local devices, ensuring higher SINR and AR values for FedAvg compared to FedProx, centralized training, and average local training. The FedAvg-based scheme achieves a cumulative improvement of 1.02 dB, 1.01 dB, and 1.01 dB in SINR, and 1.71 bps/Hz, 1.70 bps/Hz, and 1.70 bps/Hz in AR, over FedProx, centralized training, and average local training, respectively. The FedAvg outperforms FedProx, centralized training, and local training by efficiently balancing local updates and global aggregation, allowing local devices to adapt to their unique data while still contributing to a robust global model. It handles non-IID data effectively, reduces communication overhead by permitting multiple local updates before synchronization, and achieves faster convergence. In contrast, FedProx limits local model flexibility, centralized training struggles with data heterogeneity, and local training lacks global generalization. Therefore, the simulation results demonstrate the effectiveness of the proposed FedAvg scheme for the FedISAC system in 6G mmWave networks.

VI. Conclusion

In this work, we propose an AI framework that integrates the ISAC scheme with FL, where local devices send their sensing information to the GBS after completing local training. The GBS then aggregates the local sensing information and distributes the aggregated average power to the local devices according to this aggregated sensing information. We formulate an optimization problem to minimize global model loss, ensure effective power allocation, and improve both the SINR and AR. We propose an AI framework that uses the FedAvg algorithm to tackle the formulated problem and distribute the necessary power to local devices based on their sensing information. Simulation results show that the FedAvg-based AI framework delivers improvements of 1.02 dB, 1.01 dB, and 1.01 dB in SINR, and 1.71 bps/Hz, 1.70 bps/Hz, and 1.70 bps/Hz in AR, surpassing FedProx, centralized training, and average local training methods, respectively.

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