

Transformer-Based Sensing Power Allocation for OFDM ISAC Systems

Charty Joseph Gyano*, Evans Tetteh Owusu*, Clement Heanampong*,
Theodore Woode*, Kyoung-Jae Lee†, Gosan Noh*

*Dept. of Electronic Engineering, Hanbat National University, Daejeon 34158, South Korea

†School of Electrical and Electronics Engineering, Chung-Ang University, Seoul 06974, South Korea
{gyanochartyjoseph, otubrempong, cheanampong, woodetheodore}@edu.hanbat.ac.kr
kyoungjae@cau.ac.kr, gsnoh@hanbat.ac.kr

Abstract—In this work, we investigate a wideband monostatic integrated sensing and communication (ISAC) system based on orthogonal frequency division multiplexing (OFDM). The design objective is to improve communication fairness by maximizing the minimum uplink (UL) user rate while satisfying a sensing mean squared error (MSE) quality of service (QoS) requirement. To address the resulting non-convex problem, we propose an unsupervised Transformer-based sensing power allocation scheme. This scheme treats subcarriers as a sequence of tokens and learns subcarrier-dependent sensing power allocation. The proposed method is compared with uniform, maximum-sensing, and convolutional neural network (CNN) benchmarks. Simulation results demonstrate that the proposed method achieves a higher UL user rate than the benchmark schemes. This confirms the effectiveness and robustness of the proposed Transformer-based scheme for ISAC in 6G wireless systems.

Index Terms—Integrated sensing and communication, orthogonal frequency division multiplexing, Transformer, power allocation.

I. INTRODUCTION

Integrated sensing and communication (ISAC) is regarded as a key enabling technology for future wireless networks because it allows communication and sensing functions to share the same spectrum and hardware platform [1]. This integration improves spectral and hardware efficiency, but it also introduces fundamental challenges in resource allocation, i.e., the same waveform and power resources must support reliable communication and accurate sensing. Recent orthogonal frequency division multiplexing (OFDM) ISAC works have studied subcarrier power allocation for sensing and communication tradeoffs in [2] and [3] where the authors used successive convex approximation (SCA) and alternate optimization (AO), respectively, which may yield suboptimal solutions to the non-convex problem.

Learning-based methods have been widely considered for ISAC because conventional optimization methods are often intractable. The survey in [1] reviewed learning algorithms for ISAC beamforming, waveform design, spectrum allocation,

time allocation, and power allocation. In uplink (UL) communication coupled with sensing, the base station (BS) needs to process the mixed received communication and sensing signal where mutual interference exists between the two signals. The deep learning (DL)-based UL ISAC design in [4] addressed this problem by jointly designing the sensing waveform and communication receive beamforming using an unsupervised convolutional neural network (CNN) where the study focused on narrowband formulations. However, standard CNN-based models mainly exploit local feature patterns and may not fully capture global dependencies which limits the overall system performance. Also, wideband wireless channels are generally frequency selective, and OFDM is widely used to transform a frequency selective channel into multiple narrowband frequency-flat channels. Classical multi-user OFDM studies show that subcarrier-dependent power allocation can significantly improve system performance [5].

These works motivate a Transformer-based sensing power allocation to mitigate the interference between sensing and communication at the BS as a solution to the non-convex problem. A Transformer can learn global dependencies among subcarriers through the self-attention mechanism [6] to decide power allocation that minimizes interference between sensing and communication. Transformer-based designs have recently shown promise in ISAC beamforming and OFDM ISAC receiver design in [7] and [8], respectively. These works support the use of attention-based models for ISAC tasks with structured input dependencies. However, these previous Transformer-based works neglect fairness among the CUs.

In this work, we study a wideband OFDM monostatic ISAC system in which a multi-antenna BS simultaneously receives UL communication signals and sensing echoes while controlling the sensing power allocation across subcarriers using a Transformer-based algorithm that allows the Transformer to leverage global dependencies, thereby enhancing the performance of the system. Unlike weighted sum rate formulations in [4] and [9], we focus on user fairness by maximizing the minimum user rate subject to a sensing mean squared error (MSE) constraint. Fairness is considered to prevent UL users with weak channel conditions from experiencing severe rate degradation under sensing-induced interference.

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Our contributions are summarized as follows.

- We formulate a wideband OFDM monostatic ISAC sensing power allocation problem that maximizes the minimum UL user rate under a sensing MSE quality of service (QoS) constraint.
- We develop a Transformer-based ISAC architecture that treats OFDM subcarriers as sequence of tokens and learns subcarrier-dependent sensing power allocation in an unsupervised manner.
- We compare the proposed method against Uniform, Maximum-Sensing, and CNN baselines in terms of the minimum and sum rates of the UL users.

II. SYSTEM MODEL

As illustrated in Fig. 1, we consider a monostatic ISAC system with dual-function BS, K single-antenna UL communication users (CUs), and Q sensing targets. The BS has N_t sensing transmit antennas and N_r receive antennas. Specifically, on each OFDM subcarrier n , the dual-function BS first transmits the sensing waveform $\mathbf{S}[n] = [\mathbf{s}_1^T[n], \dots, \mathbf{s}_L^T[n]]^T \in \mathbb{C}^{L \times N_t}$ for target sensing, where L denotes the sensing waveform length. Then, the BS receives UL communication signals from the CUs and the target echo signals simultaneously.

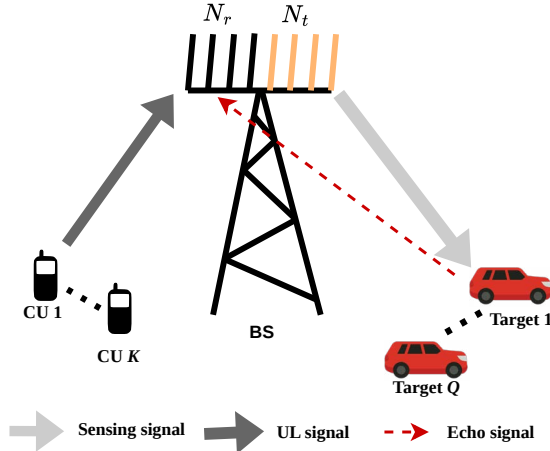


Fig. 1. OFDM uplink ISAC system.

A. Uplink Communication Channel

For user k on subcarrier n , the UL communication ideal channel is denoted by

$$\mathbf{h}_k[n] \in \mathbb{C}^{N_r \times 1}, \quad (1)$$

where $k \in \{1, \dots, K\}$ and $n \in \{1, \dots, N\}$, considering a Rayleigh fading channel. Specifically, multiple complex Gaussian delay taps are generated in the delay domain and then transformed to the frequency domain using an N -point fast Fourier transform (FFT). Therefore, each OFDM subcarrier observes a different but correlated frequency response.

The received signal at the BS on subcarrier n can be expressed as

$$\mathbf{y}_l[n] = \sum_{k=1}^K \sqrt{p_k} \mathbf{h}_k[n] x_{k,l}[n] + \mathbf{G}^T[n] \mathbf{s}_l[n] + \boldsymbol{\nu}_l[n], \quad (2)$$

where $\mathbf{y}_l[n] \in \mathbb{C}^{N_r \times 1}$ is the received signal vector at the BS during the l -th symbol interval on subcarrier n , $x_{k,l}[n]$ is the transmitted communication symbol of the k -th CU, p_k is the transmit power of user k , $\mathbf{s}_l[n] \in \mathbb{C}^{N_t \times 1}$ is the transmitted sensing waveform vector, $\mathbf{G}[n] \in \mathbb{C}^{N_t \times N_r}$ is the target response matrix (TRM), and $\boldsymbol{\nu}_l[n] \sim \mathcal{CN}(\mathbf{0}, \sigma_n^2 \mathbf{I}_{N_r})$ is the additive white Gaussian noise (AWGN) vector. After applying receive beamforming at the BS using the beamforming vector $\mathbf{w}_k[n]$, the signal to interference plus noise ratio (SINR) is modeled as

$$\gamma_k[n] = \frac{p_k |(\mathbf{w}_k[n])^H \mathbf{h}_k[n]|^2}{\sum_{j \neq k} p_j |(\mathbf{w}_k[n])^H \mathbf{h}_j[n]|^2 + (I_s[n] + \sigma_n^2) \|\mathbf{w}_k[n]\|^2}. \quad (3)$$

where $I_s[n]$ denotes the sensing interference power in [4] given by

$$I_s[n] = \frac{1}{L} \sum_{i=1}^{N_t} \sigma_{s,i}[n] \sigma_{t,i}[n]. \quad (4)$$

where $\sigma_{t,i}[n]$ is the i -th eigenvalue of the target covariance matrix (TCM). The TCM [4] is constructed as

$$\mathbf{R}_T[n] = \mathbf{G}[n] \mathbf{G}^H[n], \quad (5)$$

The eigenvalue decomposition (EVD) of $\mathbf{R}_T[n]$ is defined as

$$\mathbf{R}_T[n] = \mathbf{U}_T[n] \boldsymbol{\Sigma}_T[n] \mathbf{U}_T^H[n], \quad (6)$$

where $\boldsymbol{\Sigma}_T[n] = \text{diag}(\sigma_{t,1}[n], \dots, \sigma_{t,N_t}[n])$ contains the eigenvalues of $\mathbf{R}_T[n]$, and the columns of $\mathbf{U}_T[n]$ are the corresponding eigenvectors.

The singular value decomposition (SVD) of the sensing waveform matrix, $\mathbf{S}[n]$ is given as

$$\mathbf{S}[n] = \mathbf{U}_s[n] \boldsymbol{\Sigma}_s^{1/2}[n] \mathbf{V}_s^H[n], \quad (7)$$

where $\mathbf{U}_s[n]$ and $\mathbf{V}_s[n]$ are unitary matrices, and $\boldsymbol{\Sigma}_s[n] = \text{diag}(\sigma_{s,1}[n], \dots, \sigma_{s,N_t}[n])$ represents the sensing power allocated across the transmit sensing eigenmodes and each $\sigma_{s,i}[n]$ is the sensing power allocated to the i -th sensing eigenmode on subcarrier n . The receive beamformer, $\mathbf{w}_k[n] \in \mathbb{C}^{N_r \times 1}$ in (3) is an optimal beamformer that maximizes the communication SINR of CUs, which is given as [4],

$$\mathbf{w}_k^{\text{opt}}[n] = \frac{\tilde{\mathbf{R}}_k^{-1}[n] \mathbf{h}_k^*[n]}{\sqrt{p_k \mathbf{h}_k^T[n] \tilde{\mathbf{R}}_k^{-1}[n] \mathbf{h}_k[n]}}, \quad (8)$$

$$\tilde{\mathbf{R}}_k[n] = \sum_{i \neq k} p_i \mathbf{h}_i^*[n] \mathbf{h}_i^T[n] + \left(\frac{1}{L} \sum_{i=1}^{N_t} \sigma_{s,i}[n] \sigma_{t,i}[n] + \sigma_n^2 \right) \mathbf{I}_{N_r} \quad (9)$$

We used EVD on $\mathbf{R}_T[n]$ because it is square Hermitian positive semi-definite. Also, we used SVD on $\mathbf{S}[n]$ because it is a rectangular complex matrix. This is done to reduce the computational dimension.

The rate of user k is computed as:

$$R_k = \frac{1}{N} \sum_{n=1}^N \log_2(1 + \gamma_k[n]) \quad (10)$$

The minimum and sum rates are, respectively, given as

$$R_{\min} = \min_k R_k, \quad (11)$$

$$R_{\text{sum}} = \sum_{k=1}^K R_k. \quad (12)$$

B. Sensing Channel Model

Following the single-band TRM construction in [4], the TRM on subcarrier n , denoted by $\mathbf{G}[n] \in \mathbb{C}^{N_t \times N_r}$, is defined as:

$$\mathbf{G}[n] = \sum_{q=1}^Q \beta_q \mathbf{a}_t(\theta_q) \mathbf{b}_r^H(\theta_q), \quad (13)$$

where β_q is the complex reflection coefficient, θ_q is the target direction, and $\mathbf{a}_t(\theta_q)$ and $\mathbf{b}_r(\theta_q)$ are the transmit and receive steering vectors, respectively.

We follow the TRM estimation perspective used in the MSE-based ISAC design in [10] and the eigenvalue-domain derivation in [4] for the sensing MSE formulation. The effective inverse interference-plus-noise covariance matrix is given as

$$\mathbf{R}_H[n] = \left(\mathbf{H}[n] \tilde{\mathbf{P}} \mathbf{H}^H[n] + \sigma_n^2 \mathbf{I}_{N_r} \right)^{-1}, \quad (14)$$

where $\tilde{\mathbf{P}} \in \mathbb{R}^{K \times K}$ is the diagonal transmit power matrix of the CUs, and $\mathbf{H}[n] = [\mathbf{h}_1[n], \mathbf{h}_2[n], \dots, \mathbf{h}_K[n]] \in \mathbb{C}^{N_r \times K}$ is the UL communication channel matrix.

Under the linear Gaussian sensing model, the TRM estimation error covariance per-subcarrier can be expressed as

$$\mathbf{C}_e[n] = (\mathbf{I}_{N_r} \otimes \mathbf{R}_T^{-1}[n] + \mathbf{R}_H[n] \otimes \mathbf{S}^H[n] \mathbf{S}[n])^{-1}, \quad (15)$$

where $\otimes$ denotes the Kronecker product. The sensing MSE is given as

$$\text{MSE}(\boldsymbol{\sigma}_s) = \frac{1}{N} \sum_{n=1}^N \text{Tr}(\mathbf{C}_e[n]). \quad (16)$$

Using the EVD of $\mathbf{R}_T[n]$ and $\mathbf{R}_H[n]$, together with the SVD of $\mathbf{S}[n]$, the MSE in (16) can be written in eigenvalue form as

$$\text{MSE}(\boldsymbol{\sigma}_s) = \frac{1}{N} \sum_{n=1}^N \sum_{i=1}^{N_t} \sum_{j=1}^{N_r} (\sigma_{t,i}^{-1}[n] + \sigma_{s,i}[n] \sigma_{h,j}[n])^{-1}, \quad (17)$$

where $\sigma_{h,j}[n]$ is the j -th eigenvalue of $\mathbf{R}_H[n]$.

III. PROBLEM FORMULATION

The fairness objective is to maximize the minimum UL user rate while satisfying sensing and power constraints. The optimization variable is the sensing power vector,

$$\boldsymbol{\sigma}_s = \{\sigma_{s,i}[n] \mid n = 1, \dots, N, i = 1, \dots, N_t\}. \quad (18)$$

The optimization problem is formulated as

$$\max_{\boldsymbol{\sigma}_s} \min_k R_k \quad (19a)$$

$$\text{s.t.} \quad \text{MSE}(\boldsymbol{\sigma}_s) \leq \epsilon_{\text{mse}}, \quad (19b)$$

$$\sum_{n=1}^N \sum_{i=1}^{N_t} \sigma_{s,i}[n] \leq P_s, \quad (19c)$$

$$\sum_{i=1}^{N_t} \sigma_{s,i}[n] \leq P_{n,\max}, \quad \forall n, \quad (19d)$$

$$\sigma_{s,i}[n] \geq 0, \quad \forall n, i. \quad (19e)$$

Here, ϵ_{mse} is the sensing MSE threshold, P_s is the total sensing power budget, and $P_{n,\max}$ is the per-subcarrier sensing power threshold. Clearly, problem (19) is intractable (non-convex) because the user rate R_k (10) depends on receive beamforming, multiuser interference, and sensing-induced interference on each OFDM subcarrier via (3). Meanwhile, the sensing MSE depends on the target covariance, the communication interference-plus-noise covariance, and the sensing power assigned across subcarriers and sensing eigenmodes. Increasing the sensing power $\sigma_{s,i}[n]$ can reduce the MSE but may degrade communication performance, whereas reducing sensing power can improve communication but may violate the sensing QoS constraint.

Due to the non-convexity of the problem, fixed allocation rules are unsuitable for achieving a good communication-sensing tradeoff. This motivates a learning-based solution.

IV. PROPOSED TRANSFORMER-BASED ISAC

A. Input Representation

Each OFDM subcarrier is treated as one sequence token, and the input feature vector is constructed from communication channel information, $\mathbf{H}$, and the eigenvalues ($\boldsymbol{\Sigma}_T$) of TCM from EVD for all subcarriers N . A representative feature vector for subcarrier n is expressed as

$$\mathbf{f}[n] = \left[\Re\{\mathbf{h}_1[n]\}^T, \Im\{\mathbf{h}_1[n]\}^T, \dots, \Re\{\mathbf{h}_K[n]\}^T, \Im\{\mathbf{h}_K[n]\}^T, \sigma_{t,1}[n], \dots, \sigma_{t,N_t}[n] \right]^T. \quad (20)$$

The full input sample to the Transformer is therefore given as

$$\mathbf{F} = [\mathbf{f}[1], \dots, \mathbf{f}[N]]^T \in \mathbb{R}^{N \times d_{\text{in}}}, \quad (21)$$

where $\mathbf{F}$ is the input feature matrix of the neural network, with one feature vector for each OFDM subcarrier. d_{in} denotes the dimension of the feature vector $\mathbf{f}[n]$. Since $\mathbf{f}[n]$ contains the real and imaginary parts of the UL channel vectors of all K CUs, together with the TCM eigenvalues, its dimension is

$$d_{\text{in}} = 2N_r K + N_t. \quad (22)$$

B. Transformer Encoder

The input feature sequence is first embedded into a d dimensional latent representation, $\mathbf{Z}_0 \in \mathbb{R}^{N \times d_{\text{model}}}$ given as

$$\mathbf{Z}_0 = \mathbf{F} \mathbf{W}_e + \mathbf{P}_e, \quad (23)$$

where $\mathbf{W}_e \in \mathbb{R}^{d_{in} \times d_{model}}$ is the trainable input projection matrix, $\mathbf{P}_e \in \mathbb{R}^{N \times d_{model}}$ is the positional encoding matrix, and d_{model} is the transformer model dimension.

The attention layer forms the query, key, and value matrices and captures global dependencies as [6]

$$\text{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^T}{\sqrt{d_k}}\right) \mathbf{V}, \quad (24)$$

where $\mathbf{Q}$, $\mathbf{K}$, and $\mathbf{V}$ denote the query, key, and value matrices, respectively. d_k is the dimension of the key vector. The query and key matrices determine the attention weights between subcarriers, while the value matrix contains the subcarrier features that are weighted and aggregated. The self-attention mechanism computes pairwise dependencies among OFDM subcarrier tokens by forming attention weights from the query-key similarity matrix. As a result, the representation of each subcarrier is updated as a weighted combination of the value features from all subcarriers, enabling the Transformer network to capture global correlations between subcarriers.

C. Output Heads

The output of the Transformer encoder is passed to two output heads. The first output head produces the eigenmode allocation vector $\boldsymbol{\theta}_s[n] \in \mathbb{R}^{N_t}$ for each subcarrier, while the second output head produces the subcarrier scaling score $\eta_s[n] \in \mathbb{R}$. Following the Lambda-layer post-processing in [4], the Lambda layer first separates $\boldsymbol{\theta}_s[n]$ and $\eta_s[n]$. Then, $\boldsymbol{\theta}_s[n]$ is normalized to determine the relative sensing power distribution among the sensing eigenmodes, while $\eta_s[n]$ is scaled by the available sensing power. The predicted sensing power allocation is obtained as $\sigma_s^{\text{pred}}[n] = \eta_s[n] \frac{\boldsymbol{\theta}_s[n]}{\|\boldsymbol{\theta}_s[n]\|}$.

This post-processing enforces non-negative sensing power allocation and helps satisfy the sensing power constraints in (19c), (19d), (19e). Fig. 2 shows the proposed Transformer-based architecture.

D. Unsupervised Training Loss

The network is trained without labeled optimal allocations. Instead, the constrained optimization problem is handled using a differentiable penalty-based unsupervised loss, expressed as

$$\mathcal{L} = -R_{\min} + \lambda [\max(0, \text{MSE}(\boldsymbol{\sigma}_s) - \epsilon_{\text{mse}})]^2, \quad (25)$$

where λ is the penalty coefficient. The first term encourages fairness by increasing the minimum user rate, while the second term penalizes sensing QoS violation. This type of unsupervised loss is consistent with learning-based ISAC waveform designs that optimize communication and sensing metrics directly through a custom objective [4], [11].

V. SIMULATION RESULTS

Following [4], the sensing SNR at the BS is defined as $\text{SNR}_s = P_s \xi_0 / \sigma_n^2$; ξ_0 is the cell-edge pathloss coefficient. Similarly, the communication SNR of the k -th CU is defined as $\text{SNR}_k = p_k \xi_k / \sigma_n^2$, where ξ_k is its pathloss coefficient.

The simulation parameters are shown in Table I. For fair comparison, both the Transformer and CNN models are trained using the same unsupervised loss in (25), with 10,000 training

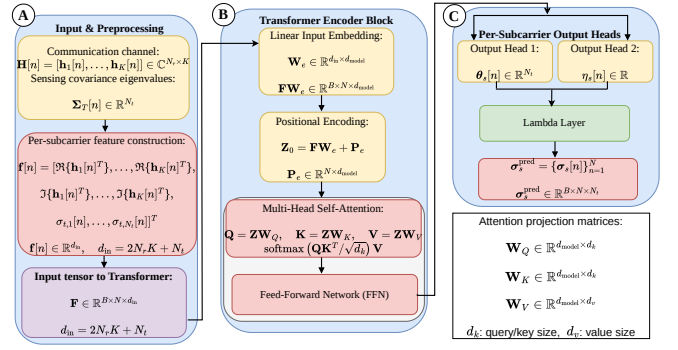


Fig. 2. Proposed Transformer Architecture for OFDM Uplink ISAC.

samples, 1,000 test samples, a batch size of 8, and 300 training epochs.

A. Benchmarks

The proposed Transformer-based algorithm is compared with the following baselines.

- *ISAC CNN*: A convolutional neural network baseline adapted from the UL “ISACNN” design in [4].
- *Uniform*: The sensing power budget is uniformly distributed across subcarriers and eigenmodes.
- *Maximum sensing*: The sensing power budget is fully used for randomly selected subcarriers where they are filled to the maximum.

TABLE I
SIMULATION PARAMETERS

Parameter	Value
Number of users, K	5
Number of targets, Q	3
Number of subcarriers, N	64
Transmit antennas, N_t	16
Receive antennas, N_r	16
Subcarrier spacing, Δf	30 kHz
Maximum sensing transmit SNR at BS	10 dB
Maximum communication transmit SNR at the CUs	0 dB

B. Performance Analysis

Fig. 3 compares the minimum CU rate of the proposed scheme against baselines as the sensing SNR is being varied. The proposed Transformer-based ISAC maintains a higher minimum rate (higher fairness) at high SNR. As sensing SNR increases, the communication-sensing tradeoff becomes stronger. The Uniform scheme suffers the most because it spreads sensing interference equally among all the subcarriers. Maximum-Sensing performs better than Uniform because it concentrates the sensing power on selected subcarriers instead of spreading it uniformly over all subcarriers. The learning-based schemes maintain higher minimum rates by adapting the sensing power allocation to the channel and sensing conditions, with the Transformer giving the best rate preservation among all the schemes. The Transformer-based model maintains a higher minimum rate because its self-attention mechanism captures global dependencies across subcarriers

and produces a more effective sensing power allocation than the CNN baseline.

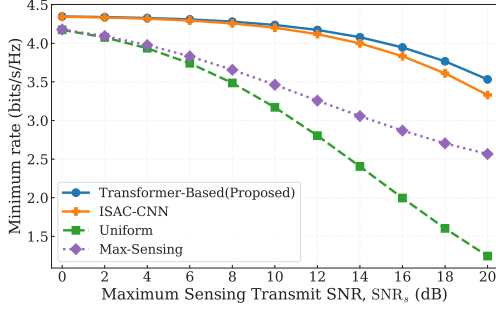


Fig. 3. Communication minimum rate versus sensing SNR.

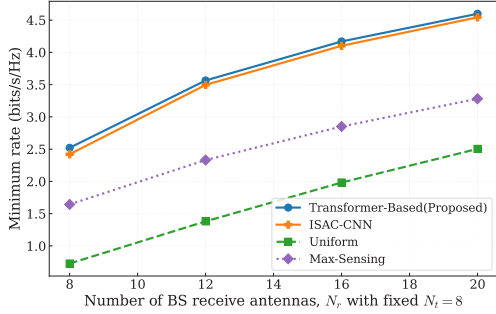


Fig. 4. Communication minimum rate versus number of receive antennas.

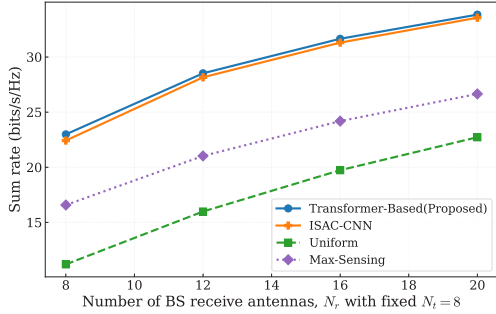


Fig. 5. Communication sum rate versus number of receive antennas.

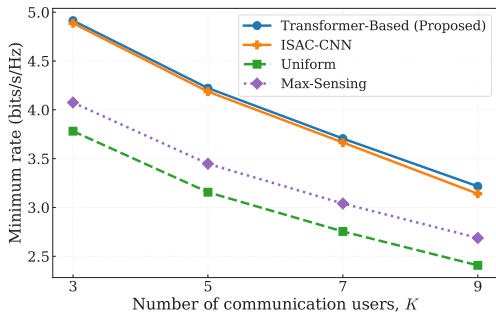


Fig. 6. Communication minimum rate versus number of users.

We also show the effect of the number of BS receive antennas on the rate performance. With N_t fixed at 8 antennas and N_r being swept over different values, the result shows how additional receive spatial degrees of freedom affect communication minimum user and sum rates, as shown respectively

in Fig. 4 and Fig. 5. With more receive antennas, the BS can combine the received signals more effectively.

It is observed that increasing the number of users, K decreases the minimum rate as shown in Fig. 6. As the user count grows, resource sharing and interference at the BS reduce the minimum rate in all schemes. However, the proposed Transformer-based scheme achieves the highest minimum user rate, demonstrating its robustness. In the reported results, the learned sensing power allocations satisfy the sensing QoS constraint $\text{MSE}(\sigma_s) \leq \epsilon_{\text{mse}}$ in (17).

VI. CONCLUSION

This paper proposed a Transformer-based unsupervised learning framework for wideband OFDM sensing power allocation in a monostatic ISAC system. The formulated problem maximizes the minimum user rate subject to sensing MSE QoS and sensing power constraints. By treating OFDM subcarriers as sequence tokens, the proposed Transformer model learns global cross-subcarrier dependencies and achieves better minimum-rate performance than the benchmark schemes. Future work will include stronger optimization-based baselines, such as SCA/AO-based methods, to compare the performance against the proposed learning-based method. We will also provide detailed computational complexity and inference-time comparisons against CNN and classical optimization schemes.

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