

Resource Allocation for Dynamic TDD-Enabled Integrated Sensing and Communication Systems

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Abstract—In this paper, we investigate a dynamic time division duplex (DTDD) enabled integrated sensing and communication (ISAC) system, in which access points (APs) mode, bandwidth and transmit power can be flexibly configured. To obtain the best tradeoff between communication and sensing performance, we maximize the sum of downlink (DL) and uplink (UL) transmission rates under the constraints of Cramer-Rao lower bound (CRLB) and the maximal transmit power by jointly optimizing the power/subcarrier allocation and APs mode selection. To deal with the proposed nonconvex problem, we adopt the alternating optimization (AO) method to divide the original problem into two subproblems. The first subproblem is related to power/subcarriers allocation, which is equivalently transformed into a Semidefinite Programming (SDP) problem and eventually solved by the penalized convex-concave procedure (PCCP) method. The second subproblem is a quadratic integer problem related to APs mode selection, which is transformed into a convex quadratic integer problem that can be efficiently solved by the convex optimization toolbox. The numerical results demonstrate the tradeoff between the total transmission rate and sensing performance with different parameter configurations. Compared with existing schemes, our proposed scheme has significant advantages in terms of tradeoff performance.

Index Terms—DTDD, ISAC system, AP mode selection, subcarrier/power allocation.

NOMENCLATURE

ω_{jn}^R	The beamforming vector for sensing
ω_{jqn}^C	The beamforming vector for communication
h_{jqn}	The channel frequency response between the j -th DL-AP and the q -th DL-UE on the n -th subcarrier
h_{uin}	The channel frequency response between the u -th UL-UE and the i -th UL-AP on the n -th subcarrier
η_p	The CRLB constraints of range
η_v	The CRLB constraints of velocity
Λ_j	The j -th AP mode selection variable

ϕ_{jn}^R	The subcarrier assignment factor for sensing
ϕ_{qn}^C	The subcarrier assignment factor for communication
τ_{jki}	The delay of the k -th target
ζ	The number of DL-APs
f_{jki}	The Doppler frequency shift of the k -th target
J	The number of APs
K	The number of targets
M	The number of OFDM symbols
N	The number of subcarriers
N_D	The number of antennas in each AP
P_C	Transmit power for DL-communication
P_R	Transmit power for sensing
P_{max}	The maximum transmit power
p_{un}	The uplink communication power
Q	The number of DL-UEs
R_{dl}	The downlink transmission rate
R_{ul}	The uplink transmission rate
U	The number of UL-UEs

I. INTRODUCTION

IT is a common vision that 6G will be a comprehensive platform integrating wireless communication, sensing and artificial intelligence [1]. The demand for more efficient spectrum utilization has propelled the integrated sensing and communication (ISAC) into the spotlight in 6G. On one hand, the communication system can leverage the same spectrum or multiplexed hardware and signal processing modules to perform diverse sensing tasks. On the other hand, the sensing outcomes can be used to enhance the communication quality.

Critical issues that need to be addressed to integrate sensing function into existing communication networks include the design of transmit waveform and the integrated receive architecture. The former primarily focuses on designing the signals transmitted from a fully shared hardware platform to simultaneously perform communication and sensing. Similar to the sensing signals design in traditional multi-input multi-output (MIMO) radar systems, the transmit beampattern of ISAC systems aims to steer the spatial power towards the intended directions or minimize the mismatch between the transmit waveform and a desired beampattern [2], [3]. In [4], transmit beamforming was optimized by minimizing the beampattern match error, taking into account individual signal-to-interference-plus-noise ratio (SINR) requirements of communication users. In addition, the work in [5] was investigated how to maximize the transmit beampattern gain towards the probing directions, while the minimum required SINR of communication users was guaranteed. The latter

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involves how to use the existing communication infrastructure to receive the echo signals. If a co-located sensing scheme is adopted, considering that the time delay of the echo signals is shorter than the symbol period, the base stations (BSs) have to operate in full-duplex (FD) mode. In this case, transmit signals pose significant interference to echo signals, rendering self-interference (SI) cancellation a pivotal challenge. While several SI cancellation techniques have been proposed in FD systems [6] [7], SI cancellation in co-located FD ISAC systems is more challenging since the strength of echo signals is much weaker than that of communication signals. An alternative approach to mitigate SI is to adopt the bistatic sensing mode, where the transmitter and radar receivers are geographically separated because increased spatial distance between transmitters and receivers can effectively alleviate SI. [8] and [9] developed a framework for perceptive mobile network (PMN), where densely deployed and synchronized remote radio units (RRUs) utilized the signals sent by BSs for collaborative perception. In [10], a network with distributed ISAC transmitters and radar receivers was studied, where a set of distributed transmitters sent individual messages to their respective communication users, while multiple sensing receivers cooperated to perform perception. However, the above ISAC systems employing dedicated radar receivers face several challenges: the high cost of deploying these receivers in existing communication networks, strong direct path interference when radar receivers are close to transmit BSs, and the potential lack of accurate reference signals in non-cooperative scenarios. In light of these issues, it is necessary to develop a superior echo receive architecture at the network level.

In distributed MIMO communication systems that support dynamic time division duplex (DTDD), the transmit and receive access points (APs) can be configured flexibly, offering a natural platform for ISAC. Unlike BSs which operate synchronously in uplink/downlink (UL/DL) modes in conventional static TDD, DTDD allows individual APs to operate independently in different modes (UL reception or DL transmission) within the same time slot. Most of the research on DTDD focuses on enhancing communication performance [11]- [12]. Some recent work has investigated ISAC schemes in cell-free networks supporting DTDD. [13] optimized the communication and sensing performance by combining the DTDD and distributed radar sensing.

In this paper, we investigate the integration of perception function into DTDD-enabled distributed MIMO systems. The transmit APs send communication and sensing signals on different subcarrier sets and different beamforming vectors are designed on different types of subcarrier sets. UL-APs receive both uplink communication information and echo signals simultaneously. The UL communication signals may be interfered by the transmitted signals from DL-APs, and the echo signals reflected by targets suffer from the direct path interference from DL-APs, as well as UL communication signals in the same frequency band. Since the CPU can know all DL/UL transmit signals, the interference mentioned above can be partially eliminated [14]. Meanwhile, the APs' mode can be flexibly configured to reduce interference and improve the tradeoff performance. We derive the Cramer-Rao Lower

Bound (CRLB) as the sensing performance metric and sum of the UL and DL transmission rate as the communication performance metric. In contrast to the work in [10] which focused solely on optimizing the transmit power, our proposed system takes a holistic approach by optimizing AP mode selection and bandwidth/power allocation, enabling a superior balance between communication and sensing performance.

The main contributions of this paper are as follows:

- A dual-function waveform based on orthogonal frequency division multiplexing (OFDM) signals is proposed by designing different beamforming vectors on the subcarriers for communication and sensing. Both the CRLBs of location and velocity estimation, as well as the sum of the UL and DL transmission rate, are analyzed.
- To achieve the best tradeoff between estimation accuracy and communication performance, we jointly optimize power/subcarrier allocation and APs mode selection to maximize the sum of the DL and UL transmission rates under the constraint of sensing performance. The mixed integer nonlinear programming (MINLP) problem is decomposed into two subproblems: one is tackled using the penalized convex-concave procedure (PCCP) method, and the other is converted into a convex quadratic integer programming, both of which are solved iteratively.
- Simulation results demonstrate the tradeoff between the total transmission rate and sensing performance with different parameter configurations. Compared with the existing scheme, our proposed approach exhibits superiority in terms of tradeoff performance.

The remainder of this paper is organized as follows. The system model is described in Section II. The communication and sensing performance are analyzed in Section III. In Section IV, the details of problem formulation and proposed algorithm are presented. We evaluate the performance of the proposed algorithm in Section V. We conclude the paper in Section VI.

II. SYSTEM MODEL

As shown in Fig. 1, we consider a DTDD-enabled MIMO ISAC system which consists of a CPU and J APs. Each AP is equipped with N_D half-duplex (HD) antennas and can perform either UL reception or DL transmission at a specific time slot. Let Λ_j represent the mode selection variable of the j -th AP. If $\Lambda_j = 1$, the j -th AP performs DL-transmission and otherwise, the j -th AP performs UL-reception.

Assume that there are U UL-UEs, Q DL-UEs, and K targets in the detection area. Each UE is equipped with one antenna. For DL transmission, DL-APs employ different subcarrier sets to transmit communication signals and detection signals. Meanwhile, to avoid mutual interference between DL-APs during detection, each DL-AP utilize a unique subcarrier set for detection. For UL reception, the UL-APs receive echo signals reflected by targets and data signals from all UL-UEs simultaneously (all UL-UEs share the same frequency band, as shown in Fig. 1), which are then conveyed to the CPU via backhaul links. DL transmission and UL reception are carried out simultaneously within the same time-frequency resources.

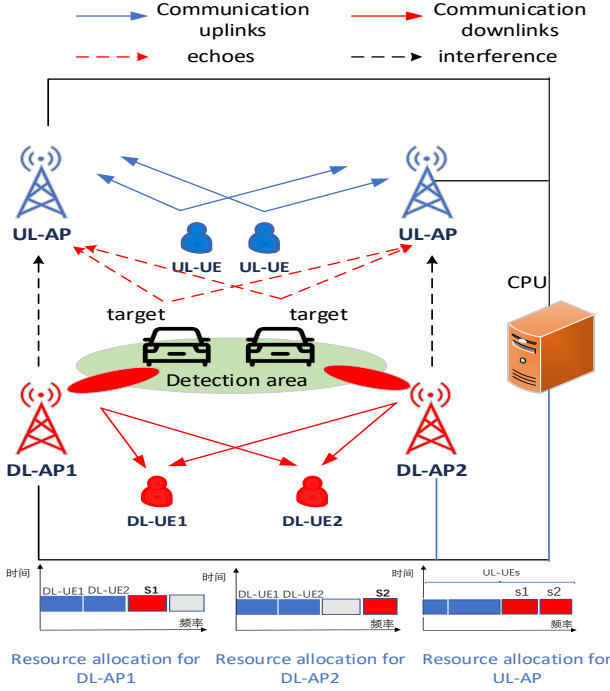


Fig. 1: DTDD-Enabled ISAC system model and time-frequency resource allocation (blue block: resource allocated to DL-UE; red block: resource allocated to sensing; gray block: unused sensing resource).

Therefore, while the system avoids SI in the individual AP, it faces interference from DL-APs to UL-APs, impacting both communication and sensing performance. Additionally, UL communication signals can also pose interference to echo signals.

The baseband signal transmitted by the j -th DL-AP on the n -th subcarrier in the m -th symbol is

$$\mathbf{s}_{jmn} = \sum_{q=1}^Q \sqrt{P_C} \phi_{qn}^C \boldsymbol{\omega}_{jqn}^C b_{qmn}^C + \sqrt{P_R} \phi_{jn}^R \boldsymbol{\omega}_{jn}^R b_{mn}^R \quad (1)$$

where P_C and P_R denote the transmit power allocated to the subcarriers for DL-communication and sensing respectively, b_{qmn}^C with $\mathbb{E}[|b_{qmn}^C|^2] = 1$ and b_{mn}^R with $\mathbb{E}[|b_{mn}^R|^2] = 1$ are the m -th OFDM baseband communication symbol transmitted to the q -th DL-UE and baseband sensing symbol, respectively, $\boldsymbol{\omega}_{jqn}^C \in \mathbb{C}^{N_D \times 1}$ is the beamforming vector for the q -th DL-UE and $\boldsymbol{\omega}_{jn}^R \in \mathbb{C}^{N_D \times 1}$ is the beamforming vector for illuminating the probing area respectively, and $\phi_{qn}^C \in \{0, 1\}$ and $\phi_{jn}^R \in \{0, 1\}$ are subcarrier assignment factors. To avoid mutual interference between communication and sensing signals, each subcarrier is exclusively allocated to either communication or detection, i.e., $\sum_{q=1}^Q \phi_{qn}^C + \sum_{j=1}^J \phi_{jn}^R = 1, \forall n$.

To improve the detection performance, we assume that DL-APs will illuminate the same region cooperatively with designed wide beam on detection subcarriers. Define $\boldsymbol{\Gamma}_{jn} = \boldsymbol{\omega}_{jn}^R \boldsymbol{\omega}_{jn}^{R^H}$. By relaxing the rank-1 constraint of $\boldsymbol{\Gamma}_{jn}$, the beampattern on each detection subcarrier is generated by solving the following constrained least-squares (LS) problem

[4],

$$\begin{aligned} \min_{\eta_{jn}, \boldsymbol{\Gamma}_{jn}} & \sum_{l=1}^L |\eta_{jn} P_j(\theta_l) - \mathbf{a}_n^H(\theta_l) \boldsymbol{\Gamma}_{jn} \mathbf{a}_n(\theta_l)|^2 \\ \text{s.t.} & \begin{cases} \sum_{i=1}^{N_D} [\boldsymbol{\Gamma}_{jn}]_{i,i} = 1, \\ \boldsymbol{\Gamma}_{jn} \succeq 0, \boldsymbol{\Gamma}_{jn} = \boldsymbol{\Gamma}_{jn}^H \\ \eta_{jn} \geq 0 \end{cases} \end{aligned} \quad (2)$$

where η_{jn} is a scaling factor, $\{\theta_l\}_{l=1}^L$ denote equally spaced angular grids covering the probing range, L is the number of sample angles, $\mathbf{a}_n(\theta_l) = [1, e^{-j\frac{2\pi}{\lambda_n} d \sin \theta_l}, \dots, e^{-j\frac{2\pi}{\lambda_n} (N_D-1) d \sin \theta_l}]^T$, $P_j(\theta_l)$ denotes the desired beampattern gain of the j -th DL-AP at θ_l , d is the spacing between antenna elements, $\lambda_n = \frac{c}{f_c + (n-1)\Delta f}$ is the wavelength on the n -th subcarrier, and Δf is the frequency interval of adjacent subcarriers. Considering the differences in relative location between detection area and different DL-APs, we use Φ_j to represent the detection angular range of the j -th DL-AP. That is, $P_j(\theta_l) = 1$ when $\theta_l \in \Phi_j$, otherwise $P_j(\theta_l) = 0$. Once the optimal solution $\boldsymbol{\Gamma}_{jn}^*$ is obtained, the beamforming vector $\boldsymbol{\omega}_{jn}^R$ can be generated by Gaussian randomization in [15].

The transmitted signal block consists of N subcarriers and M OFDM symbols with symbol duration $T_s = T + T_{cp}$, where $T = \frac{1}{\Delta f}$ is the OFDM symbol period, T_{cp} is the length of cyclic prefix (CP). After inverse fast Fourier transform (IFFT), adding CP, and impulse shaping, the baseband complex waveform of the j -th DL-AP is

$$\mathbf{x}_j(t) = \sum_{m=1}^M \sum_{n=1}^N \mathbf{s}_{jmn} e^{j2\pi n \Delta f t} u(t - (m-1)T_s) \quad (3)$$

where

$$u(t) = \begin{cases} 1, & t \in [-T_{cp}, T] \\ 0, & \text{otherwise.} \end{cases} \quad (4)$$

III. ANALYSIS OF COMMUNICATION AND SENSING PERFORMANCE

In this section, we analyze the UL and DL communication and sensing performance of DTDD-enabled distributed MIMO systems.

A. Downlink Communication Performance

In the DL transmission, all DL-APs serve for DL-UEs cooperatively under the control of the CPU. Therefore, each DL-UE receives signals from all DL-APs and the received signal of the q -th DL-UE on the n -th subcarrier in the m -th OFDM symbol can be expressed as

$$\mathbf{y}_{qmn} = \sum_{j=1}^J \Lambda_j \mathbf{h}_{jqn}^T \boldsymbol{\omega}_{jqn}^C \sqrt{P_C} \phi_{qn}^C b_{qmn}^C + \mathbf{n}_{dl} \quad (5)$$

where $\mathbf{h}_{jqn} = \sqrt{\frac{\lambda^2}{(4\pi)^2 d_{jq}^2}} (\mathbf{a}_n(\beta_{jq}) + \sum_{a=1}^{A_0} \epsilon_{jaq} e^{-j\frac{2\pi n a}{N}})$ is the channel frequency response between the j -th DL-AP and the q -th DL-UE on the n -th subcarrier, d_{jq} is the distance between the j -th DL-AP and the q -th DL-UE, A_0 is the number of

multipath, ϵ_{jaq} is the small-scale complex vector of the a -th multipath between the q -th DL-UE and the j -th DL-AP, $\mathbf{a}_n(\beta_{jq}) = [1, e^{-j\frac{2\pi}{\lambda_n}d \sin \beta_{jq}}, \dots, e^{-j\frac{2\pi}{\lambda_n}d(N_D-1) \sin \beta_{jq}}]^T$, β_{jq} is the angle of departure (AoD) from the j -th DL-AP to the q -th DL-UE, $\mathbf{n}_{dl}$ is the additive white Gaussian noise (AWGN) with zeros mean and variance σ_{dl}^2 . The transmitters adopt maximum ratio transmission (MRT) to maximize the received signal-to-noise ratio (SNR), i.e., $\omega_{jqn}^C = \frac{\mathbf{h}_{jqn}}{\|\mathbf{h}_{jqn}\|}$. Therefore, the SNR of the q -th DL-UE on the n -th subcarrier is

$$\gamma_{qn} = \frac{(\sum_{j=1}^J \Lambda_j \|\mathbf{h}_{jqn}\|)^2 P_C}{\sigma_{dl}^2}. \quad (6)$$

The DL transmission rate of the q -th DL-UE on the n -th subcarrier is $R_{qn}^{dl} = \log(1 + \gamma_{qn})$. Then, the total transmission rate of DL transmission is

$$R_{dl} = \sum_{q=1}^Q \sum_{n=1}^N \phi_{qn}^C R_{qn}^{dl}. \quad (7)$$

B. Uplink Communication Performance

For UL reception, each UL-AP receives information symbols from all UL-UEs and interference signals from DL-APs. The received signals of the i -th UL-APs on the n -th subcarrier in the m -th OFDM symbol can be expressed as

$$\mathbf{y}_i^{mn} = \sum_{u=1}^U \sqrt{p_{un}} \mathbf{h}_{uin} x_{umn} + \sum_{j=1}^J \Lambda_j \mathbf{G}_{Iji} \mathbf{s}_{jmn} + \mathbf{n}_{ul} \quad (8)$$

where $\mathbf{h}_{uin} = \sqrt{\frac{\lambda^2}{(4\pi)^2 d_{ui}^2}} (\mathbf{a}_n(\beta_{ui}) + \sum_{a=1}^{A_1} \epsilon_{uai} e^{-j\frac{2\pi n a}{N}})$ is the channel frequency response between the u -th UL-UE and the i -th UL-AP on the n -th subcarrier, d_{ui} is the relative distance between the u -th UL-UE and the i -th UL-AP, A_1 is the number of multipath, ϵ_{uai} denotes the small-scale complex vector of the a -th multipath between the u -th UL-UE and the i -th UL-AP, $\mathbf{a}_n(\beta_{ui}) = [1, e^{-j\frac{2\pi}{\lambda_n}d \sin \beta_{ui}}, \dots, e^{-j\frac{2\pi}{\lambda_n}d(N_D-1) \sin \beta_{ui}}]^T$ is the receive steering vector of direct path, β_{ui} is the angle of arrival (AoA) from the u -th UL-UE to the i -th UL-AP, x_{umn} is the UL communication symbol transmitted by the u -th UL-UE with $\mathbb{E}[|x_{umn}|^2] = 1$, $\mathbf{G}_{Iji}$ denotes the channel between the j -th DL-AP and the i -th UL-AP and $\mathbf{n}_{ul}$ is AWGN with zero mean and covariance $\sigma_{ul}^2 \mathbf{I}$. Since the signals transmitted by DL-APs are accessible to the CPU, the interference from DL-APs can be completely canceled if the inter-AP channels are perfectly estimated. However, in practical scenarios, acquiring precise channel information is challenging. Therefore, we denote $\mathbf{E}_{Iji}$ as the channel estimation error matrix with $\mathbf{E}_{Iji} \sim \mathcal{CN}(0, \sigma_I^2 \mathbf{I}_{N_D \times N_D})$ (σ_I^2 represents the power of estimation error).

At the CPU, to extract information symbols from the u -th UL-UE, after inter-AP interference cancellation, signals from all UL-APs are passed through a linear combiner to get

$$\begin{aligned} \tilde{x}_{umn} = & \sum_{i=1}^J (1 - \Lambda_i) \mathbf{v}_{uin}^H \left(\sum_{u=1}^U \sqrt{p_{un}} \mathbf{h}_{uin} x_{umn} \right. \\ & \left. + \sum_{j=1}^J \Lambda_j \mathbf{E}_{Iji} \mathbf{s}_{jmn} + \mathbf{n}_{ul} \right) \end{aligned} \quad (9)$$

Assume that zero force (ZF) receiver is adopted at the CPU for UL reception. For the ZF receiver, $\mathbf{v}_{uin}$ is the u -th column of $\mathbf{H}_{in}(\mathbf{H}_{in}^H \mathbf{H}_{in})^{-1}$ where $\mathbf{H}_{in} = [\mathbf{h}_{1in}, \dots, \mathbf{h}_{Uin}]$. Note here we assume that $U \leq N_D$. Based on (9), the SINR of the u -th UL-UE is

$$\gamma_{un} = \frac{|\sum_{i=1}^J (1 - \Lambda_i) \mathbf{v}_{uin}^H \mathbf{h}_{uin}|^2 p_{un}}{\sum_{i=1}^J (1 - \Lambda_i) I_{uin}} \quad (10)$$

where

$$\begin{aligned} I_{uin} = & \sum_{u'=1, u' \neq u}^U |\mathbf{v}_{uin}^H \mathbf{h}_{u'in}|^2 p_{u'n} \\ & + \sigma_I^2 \|\mathbf{v}_{uin}^H \sum_{j=1}^J \Lambda_j \left(\sum_{q=1}^Q \sqrt{P_C} \phi_{qn}^C \omega_{jqn}^C + \sqrt{P_R} \phi_{jn}^R \omega_{jn}^R \right) \|^2 \\ & + \sigma_{ul}^2 \|\mathbf{v}_{uin}^H\|^2 \end{aligned} \quad (11)$$

To simplify the optimization problem, I_{uin} is bounded by

$$\begin{aligned} I_{uin} \leq & \sum_{u'=1, u' \neq u}^U |\mathbf{v}_{uin}^H \mathbf{h}_{u'in}|^2 p_{u'n} \\ & + \sigma_I^2 P_{max} \|\mathbf{v}_{uin}^H\|^2 + \sigma_{ul}^2 \|\mathbf{v}_{uin}^H\|^2 \end{aligned} \quad (12)$$

where P_{max} is the transmit power constraint of J APs. The total transmission rate of UL transmission is given by

$$R_{ul} = \sum_{n=1}^N \sum_{u=1}^U \log(1 + \gamma_{un}) \quad (13)$$

C. Sensing Performance

Suppose that there are K moving targets within the probing area. When targets are illuminated by detection signals transmitted by DL-APs, UL-APs receive echo signals reflected by targets. Considering that echo signals may be interfered by clutter, direct path signals from DL-APs and UL communication signals within the same frequency band, it is necessary to subtract the UL communication signals from received signals after correctly decoding them, and then perform clutter suppression. After interference cancellation, clutter suppression and matched filtering, the signal received by the i -th UL-AP on the n -th subcarrier in the m -th OFDM symbol can be expressed as $\mathbf{y}_{imn}^R = [\mathbf{y}_{1imn}^R, \dots, \mathbf{y}_{jimn}^R, \dots, \mathbf{y}_{Jimn}^R]^T$, where

$$\begin{aligned} \mathbf{y}_{jimn}^R = & (1 - \Lambda_i) \left(\sum_{k=1}^K \Lambda_j c_{jki} \sqrt{P_R} \phi_{jn}^R e^{j2\pi m T f_{jki}} \right. \\ & \left. e^{-j2\pi n \Delta f \tau_{jki}} \mathbf{a}_r(\alpha_{ik}) \mathbf{a}_t^T(\beta_{kj}) \omega_{jn}^R \mathbf{b}_{mn}^R \right) \\ & + \sum_{u=1}^U \sqrt{p_{un}} \mathbf{e}_{uin} + \mathbf{E}_{Iji}^R \mathbf{s}_{jmn} + \mathbf{n}_r \end{aligned} \quad (14)$$

where $c_{jki} = \sqrt{\frac{\lambda^2 R C S_{jki}}{(4\pi)^3 \|\mathbf{d}_j - \mathbf{d}_k\|^2 \|\mathbf{d}_k - \mathbf{d}_i\|^2}}$, $f_{jki} = \frac{\mathbf{v}_k^T (\mathbf{d}_j - \mathbf{d}_k)}{\lambda \|\mathbf{d}_j - \mathbf{d}_k\|} + \frac{\mathbf{v}_k^T (\mathbf{d}_i - \mathbf{d}_k)}{\lambda \|\mathbf{d}_i - \mathbf{d}_k\|}$ and $\tau_{jki} = \frac{\|\mathbf{d}_j - \mathbf{d}_k\| + \|\mathbf{d}_k - \mathbf{d}_i\|}{c}$, denote propagation loss, Doppler frequency and time delay from the j -th DL-AP to the i -th UL-AP via the k -th target respectively, $\mathbf{d}_k = [d_k^x, d_k^y]^T$ and $\mathbf{v}_k = [v_k^x, v_k^y]^T$ denote the location and

velocity of the k -th target, $\mathbf{d}_j = [d_j^x, d_j^y]^T$ and $\mathbf{d}_i = [d_i^x, d_i^y]^T$ denote the locations of the j -th DL-AP and the i -th UL-AP, $\mathbf{a}_r(\alpha_{ik}) \in \mathbb{C}^{N_D \times 1}$, $\mathbf{a}_t(\beta_{kj}) \in \mathbb{C}^{N_D \times 1}$ are steering vectors with $\mathbf{a}_r(\alpha_{ik}) = \left[1, e^{-j\frac{2\pi}{\lambda_n} d \sin \alpha_{ik}}, \dots, e^{-j\frac{2\pi}{\lambda_n} d(N_D-1) \sin \alpha_{ik}}\right]^T$, $\mathbf{a}_t(\beta_{kj}) = \left[1, e^{-j\frac{2\pi}{\lambda_n} d \sin \beta_{kj}}, \dots, e^{-j\frac{2\pi}{\lambda_n} d(N_D-1) \sin \beta_{kj}}\right]^T$, $\beta_{kj} = \arctan(\frac{d_j^y - d_i^y}{d_k^x - d_i^x})$ and $\alpha_{ik} = \arctan(\frac{d_k^y - d_i^y}{d_k^x - d_i^x})$ are AoD from the j -th DL-AP to the k -th target and AoA from the k -th target to the i -th UL-AP respectively, $\mathbf{e}_{uin} \sim \mathcal{CN}(0, \sigma_e^2 \mathbf{I})$ is the residual interference of UL communication signals due to demodulation or channel estimation errors, $\mathbf{E}_{Iji}^R$ is the inter-APs channel estimation error matrix with $\mathbf{E}_{Iji}^R \sim \mathcal{CN}(0, \sigma_I^2 \mathbf{I})$, and $\mathbf{n}_r$ is AWGN with zero mean and covariance $\sigma_r^2 \mathbf{I}$.

We employ the CRLB of estimation parameters as the metric of sensing performance. Let $\mathbf{u} = [\mathbf{u}_1^T, \dots, \mathbf{u}_K^T, \mathbf{c}]^T$, where $\mathbf{u}_k = [d_k^x, d_k^y, v_k^x, v_k^y]^T$ and $\mathbf{c} = [c_{111}, \dots, c_{jki}, \dots, c_{JKJ}]$, and let $\boldsymbol{\gamma} = [\boldsymbol{\varphi}_1, \dots, \boldsymbol{\varphi}_K, \mathbf{c}]$, where $\boldsymbol{\varphi}_k = [\varphi_{1k1}, \dots, \varphi_{jki}, \dots, \varphi_{JKJ}]$, $\varphi_{jki} = [\tau_{jki}, f_{jki}, \alpha_{ik}, \beta_{kj}]$. Since $\mathbf{y} = [\mathbf{y}_1^T, \dots, \mathbf{y}_j^T, \dots, \mathbf{y}_J^T]^T$, where $\mathbf{y}_j = [(\mathbf{y}_{j111}^R)^T, \dots, (\mathbf{y}_{jimn}^R)^T, \dots, (\mathbf{y}_{jJMN}^R)^T]^T$ is a Gaussian vector with mean $\boldsymbol{\mu} = [\boldsymbol{\mu}_1^T, \dots, \boldsymbol{\mu}_j^T, \dots, \boldsymbol{\mu}_J^T]^T$, where $\boldsymbol{\mu}_j = [(\boldsymbol{\mu}_{j111}^R)^T, \dots, (\boldsymbol{\mu}_{jimn}^R)^T, \dots, (\boldsymbol{\mu}_{jJMN}^R)^T]^T$ and covariance matrix $\sigma^2 \mathbf{I}_{N_D J^2 MN \times N_D J^2 MN}$, we can calculate the Fisher Information Matrix (FIM) $\mathbf{F}(\boldsymbol{\gamma})$ with respect to $\boldsymbol{\gamma}$,

$$\mathbf{F}(\boldsymbol{\gamma}) = \frac{2}{\sigma^2} \text{Re} \left(\frac{\partial \boldsymbol{\mu}}{\partial \boldsymbol{\gamma}} \frac{\partial \boldsymbol{\mu}}{\partial \boldsymbol{\gamma}} \right) \quad (15)$$

where $\sigma^2 \approx \sigma_r^2 + \sum_{u=1}^U p_{un} \sigma_e^2 + P_{max} \sigma_I^2$ by using the same approximation as (11). According to the chain rule, the FIM $\mathbf{F}(\mathbf{u})$ with respect to $\mathbf{u}$ can be calculated as

$$\mathbf{F}(\mathbf{u}) = \mathbf{J} \mathbf{F}(\boldsymbol{\gamma}) \mathbf{J}^T \quad (16)$$

where $\mathbf{J}$ is the following Jacobian matrix

$$\mathbf{J} = \frac{\partial \boldsymbol{\gamma}}{\partial \mathbf{u}} = \begin{bmatrix} \mathbf{J}_1 & \cdots & \mathbf{0} & \mathbf{0} \\ \vdots & \ddots & \vdots & \vdots \\ \mathbf{0} & \cdots & \mathbf{J}_K & \mathbf{0} \\ \mathbf{0} & \cdots & \mathbf{0} & \mathbf{I}_0 \end{bmatrix} \quad (17)$$

and $\mathbf{I}_0$ is a $J^2 K \times J^2 K$ unit matrix, $\mathbf{J}_k = [\mathbf{J}_{1k1}, \dots, \mathbf{J}_{jki}, \dots, \mathbf{J}_{JKJ}]$ where

$$\mathbf{J}_{jki} = \begin{bmatrix} \frac{\partial \tau_{jki}}{\partial d_k^x} & \frac{\partial f_{jki}}{\partial d_k^x} & \frac{\partial \alpha_{ik}}{\partial d_k^x} & \frac{\partial \beta_{kj}}{\partial d_k^x} \\ \frac{\partial \tau_{jki}}{\partial d_k^y} & \frac{\partial f_{jki}}{\partial d_k^y} & \frac{\partial \alpha_{ik}}{\partial d_k^y} & \frac{\partial \beta_{kj}}{\partial d_k^y} \\ 0 & \frac{\partial f_{jki}}{\partial v_k^x} & 0 & 0 \\ 0 & \frac{\partial f_{jki}}{\partial v_k^y} & 0 & 0 \end{bmatrix}. \quad (18)$$

By ignoring interference between targets, $\mathbf{F}(\boldsymbol{\gamma})$ in (15) is a block diagonal matrix, so that $\mathbf{F}(\mathbf{u})$ is also a block diagonal matrix. The detailed derivation of $\mathbf{F}(\mathbf{u})$ is given in the Appendix. Consequently, the lower bound of CRLB of the k -th target is given by

$$[\mathbf{F}_k(\mathbf{u})]^{-1} = \left(\frac{2}{\sigma^2} \sum_{i=1}^J \sum_{j=1}^J \sum_{n=1}^N \sum_{m=1}^M \Lambda_j (1 - \Lambda_i) P_R \phi_{jn}^R \boldsymbol{\Psi}_k \right)^{-1} \quad (19)$$

where

$$\boldsymbol{\Psi}_k(i, j, n, m) = \begin{bmatrix} \mathbf{P}_k(i, j, n, m) & \mathbf{0} \\ \mathbf{0} & \mathbf{V}_k(i, j, n, m) \end{bmatrix} \quad (20)$$

Both $\mathbf{P}_k(i, j, n, m)$ and $\mathbf{V}_k(i, j, n, m)$ are 2×2 matrices, whose expressions are provided in Appendix. Then, we can obtain the lower bound of CRLB of the k -th target's location and velocity by calculating

$$\mathbf{C}_k^p = \left(\frac{2}{\sigma^2} \sum_{i=1}^J \sum_{j=1}^J \sum_{n=1}^N \sum_{m=1}^M \Lambda_j (1 - \Lambda_i) P_R \phi_{jn}^R \mathbf{P}_k(i, j, n, m) \right)^{-1} \quad (21)$$

$$\mathbf{C}_k^v = \left(\frac{2}{\sigma^2} \sum_{i=1}^J \sum_{j=1}^J \sum_{n=1}^N \sum_{m=1}^M \Lambda_j (1 - \Lambda_i) P_R \phi_{jn}^R \mathbf{V}_k(i, j, n, m) \right)^{-1} \quad (22)$$

IV. PROBLEM FORMULATION AND SOLUTION

A. Problem Formulation

In the previous section, we have analyzed UL and DL communication rates, as well as the CRLB for target parameter estimation under the condition of imperfect interference cancellations. The analysis reveals that both communication and sensing performance are influenced by power/subcarriers allocation and APs mode selections. Therefore, in this section, we investigate the optimal resource allocation and mode selection scheme to achieve the tradeoff between communication and sensing performance. To maximize the sum transmission rate under the constraints of CRLB, the problem is formulated as

$$\max_{\mathcal{P}} R_{dl} + R_{ul} \quad (23)$$

$$\text{s.t. } [\mathbf{C}_k^p]_{1,1} \leq \eta_p, [\mathbf{C}_k^p]_{2,2} \leq \eta_p, \forall k \quad (23a)$$

$$[\mathbf{C}_k^v]_{1,1} \leq \eta_v, [\mathbf{C}_k^v]_{2,2} \leq \eta_v, \forall k \quad (23b)$$

$$\sum_{j=1}^J \Lambda_j \left(\sum_{q=1}^Q \sum_{n=1}^N \phi_{qn}^C P_C + \sum_{n=1}^N \phi_{jn}^R P_R \right) \leq P_{max} \quad (23c)$$

$$P_C \geq 0, P_R \geq 0 \quad (23d)$$

$$\sum_{j=1}^J \Lambda_j \left(\sum_{q=1}^Q \phi_{qn}^C + \phi_{jn}^R \right) = 1, \forall n \quad (23e)$$

$$\phi_{qn}^C \in \{0, 1\}, \phi_{jn}^R \in \{0, 1\}, \forall q, j, n \quad (23f)$$

$$\sum_{j=1}^J \Lambda_j = \zeta \quad (23g)$$

$$\Lambda_j \in \{0, 1\}, \forall j \quad (23h)$$

where $\mathcal{P} = \left\{ \{\phi_{jn}^R\}_{j=1, n=1}^{J, N}, \{\phi_{qn}^C\}_{q=1, n=1}^{Q, N}, P_C, P_R, \boldsymbol{\Lambda} \right\}$, $\boldsymbol{\Lambda} = [\Lambda_1, \dots, \Lambda_J]$. The constraints in (23a) and (23b) represent the requirements for location and velocity estimations accuracy for all targets. (23c) and (23d) are the total power constraint and power constraints on each subcarrier respectively. (23e) and (23f) are constraints of subcarrier assignment factors. (23g) is the constraint of APs' number ζ pre-selected for transmission. (23h) is the constraint of APs mode selection factors.

B. Solution to (23)

The problem in (23) is a Mixed Integer Nonlinear Programming (MINLP) problem. To tackle the non-convex constraints, we adopt the alternating optimization (AO) method to solve (23), which is decomposed into two subproblems (24) and (25). For given APs mode selections, we address the following subproblem (24) to obtain the optimal power and subcarrier allocation,

$$\begin{aligned} \max_{\mathcal{P}_1} \quad & R_{dl} \\ \text{s.t.} \quad & (23a) - (23f) \end{aligned} \quad (24)$$

where $\mathcal{P}_1 = \left\{ \{\phi_{jn}^R\}_{j=1,n=1}^{J,N}, \{\phi_{qn}^C\}_{q=1,n=1}^{Q,N}, P_C, P_R \right\}$. Then, for given optimal power/subcarrier allocation, we solve the following subproblem (25) to obtain the optimal APs mode selection,

$$\begin{aligned} \max_{\Lambda} \quad & R_{dl} + R_{ul} \\ \text{s.t.} \quad & (23a) - (23c), (23e), (23g), (23h) \end{aligned} \quad (25)$$

Subproblems (24) and (25) are optimized alternately until the optimal solution converges. The details of solving (24) and (25) are provided below.

1) *optimal power/subcarrier allocation*: In this part, we explore the solution to subproblem (24). Firstly, to eliminate the non-convex coupling between (P_C, P_R) and $(\phi_{qn}^C, \phi_{jn}^R)$, we substitute the variables $\hat{P}_{qn}^C = P_C \phi_{qn}^C$ and $\hat{P}_{jn}^R = P_R \phi_{jn}^R$ to transform the objective function R_{dl} into the convex function of $\hat{P}_{qn}^C$. Then, we can transform (23a) and (23b) into convex constraints of $\hat{P}_{jn}^R$ through matrix transformation [16]. For convenience, we define $\mathbf{C}_k^p = \begin{bmatrix} C_{11} & C_{12} \\ C_{21} & C_{22} \end{bmatrix}^{-1}$.

Construct the matrix $\hat{\mathbf{C}}_k^{px} = \begin{bmatrix} C_{22} & C_{12}\sqrt{\eta_p} \\ C_{21}\sqrt{\eta_p} & C_{11}\eta_p - 1 \end{bmatrix}$ and $\hat{\mathbf{C}}_k^{py} = \begin{bmatrix} C_{11} & C_{12}\sqrt{\eta_p} \\ C_{21}\sqrt{\eta_p} & C_{22}\eta_p - 1 \end{bmatrix}$. The constraints in (23a) are equivalent to

$$\hat{\mathbf{C}}_k^{px} \succeq 0, \hat{\mathbf{C}}_k^{py} \succeq 0 \quad (26)$$

Similarly, the constraints in (23b) can be converted into

$$\hat{\mathbf{C}}_k^{vx} \succeq 0, \hat{\mathbf{C}}_k^{vy} \succeq 0 \quad (27)$$

The binary constraints in (23f) can be transformed to the continuous variable constraints in the following manner

$$\phi_{qn}^C \in [0, 1], \phi_{jn}^R \in [0, 1], \forall q, j, n \quad (28)$$

$$\phi_{qn}^C(1 - \phi_{qn}^C) \leq 0, \phi_{jn}^R(1 - \phi_{jn}^R) \leq 0, \forall q, j, n \quad (29)$$

Note that the left-hand side of constraints in (29) is the form of difference-of-convex (DC) with respect to the variables $(\phi_{qn}^C, \phi_{jn}^R)$, which can be addressed by using the penalized convex-concave procedure (PCCP) [17]. First, we add slack variables to the constraints in (29),

$$\phi_{qn}^C(1 - \phi_{qn}^C) \leq \rho_{qn}, \phi_{jn}^R(1 - \phi_{jn}^R) \leq \theta_{jn}, \forall q, j, n \quad (30)$$

$$\rho_{qn} \geq 0, \theta_{jn} \geq 0, \forall q, j, n \quad (31)$$

Next, by applying the first-order Taylor expansion at the given point $(\phi_{qn}^{C(i)}, \phi_{jn}^{R(i)})$ where i denotes the iteration index of the PCCP method, we linearize the constraints in (30) as follows

$$(\phi_{qn}^{C(i)})^2 + \phi_{qn}^C(1 - 2\phi_{qn}^{C(i)}) \leq \rho_{qn}, \forall q, n \quad (32)$$

$$(\phi_{jn}^{R(i)})^2 + \phi_{jn}^R(1 - 2\phi_{jn}^{R(i)}) \leq \theta_{jn}, \forall j, n \quad (33)$$

Finally, the subproblem in (24) can be solved by iteratively solving the following convex problem,

$$\begin{aligned} \max_{\mathcal{P}_2} \quad & R_{dl} - \varepsilon^{(i)} \left(\sum_{n=1}^N \sum_{q=1}^Q \rho_{qn} + \sum_{j=1}^J \sum_{n=1}^N \theta_{jn} \right) \\ \text{s.t.} \quad & (23d), (23e), (26) - (28), (31) - (33) \end{aligned} \quad (34)$$

$\mathcal{P}_2 \triangleq \left\{ \{\phi_{qn}^C, \hat{P}_{qn}^C, \rho_{qn}\}_{q=1,n=1}^{Q,N}, \{\phi_{jn}^R, \hat{P}_{jn}^R, \theta_{jn}\}_{j=1,n=1}^{J,N} \right\}$, $\varepsilon^{(i)} > 0$ is the penalty coefficient in the i -th iteration. The penalty term in the objective is to force $(\sum_{n=1}^N \sum_{q=1}^Q \rho_{qn} + \sum_{j=1}^J \sum_{n=1}^N \theta_{jn}) \rightarrow 0$.

We outline the algorithm for solving the subproblem (34) in Algorithm 1.

Algorithm 1 Algorithm for Solving Problem in (34)

- 1: Initialization: $\mathcal{P}_2^{(0)}, \varepsilon_{max}, \varepsilon^{(0)} > 0, \nu > 1$, tolerance $\Delta = 10^{-5}$, the iteration counter $i = 0$, the maximum number of iterations I_{max} .
 - 2: **repeat**
 - 3: Obtain the optimal solution $\mathcal{P}_2^*$ and value of objective $R_{dl}^{(i)}$ by solving (34).
 - 4: Set $i \leftarrow i + 1$
 - 5: update $\mathcal{P}_2^{(i)} \leftarrow \mathcal{P}_2^*$.
 - 6: Set $\varepsilon^{(i+1)} \leftarrow \min \{\nu \varepsilon^{(i)}, \varepsilon_{max}\}$.
 - 7: **until** $|R_{sum}^{(i)} - R_{sum}^{(i-1)}| \leq \Delta$ or $i = I_{max}$.
 - 8: **Output**: $\mathcal{P}_2$.
-

2) *optimal APs mode selections scheme*: In this part, we explore methods to tackle the subproblem (25) with given power/subcarrier allocation. To convert the objective function in (25) into a convex function of Λ , we reformulate the UL and DL transmission rates as

$$R_{ul} = \sum_{u=1}^U \sum_{n=1}^N (\log(a_{un}) - \log(I_{un})) \quad (35)$$

$$R_{dl} = \sum_{q=1}^Q \sum_{n=1}^N \phi_{qn}^C (\log(c_{qn}) - \log(\sigma_{dl}^2)) \quad (36)$$

where $a_{un} = \sum_{i=1}^J \sum_{i'=1}^J b_{ii'} (\mathbf{v}_{uin}^H \mathbf{h}_{uin}) (\mathbf{v}_{uj'n}^H \mathbf{h}_{ui'n})^* p_{un} + I_{un}$, $b_{ii'} = (1 - \Lambda_i)(1 - \Lambda_{i'})$, $I_{un} = \sum_{i=1}^J (1 - \Lambda_i) I_{uin}$, $c_{qn} = \sum_{j=1}^J \sum_{j'=1}^J d_{jj'} \|\mathbf{h}_{jqn}\| \|\mathbf{h}_{j'qn}\| P_C + \sigma_{dl}^2$, $d_{jj'} = \Lambda_j \Lambda_{j'}$. When $\{\Lambda_i\}_{i=1}^J$ are binary variables, $b_{ii'}$ and $d_{jj'}$ are binary variables. The non-linear equality constraints between $b_{ii'}$, $d_{jj'}$ and Λ can be equivalently transformed into the following linear inequation constraints,

$$\begin{cases} b_{ii'} \leq 1 - \Lambda_i, \forall i, i' \\ b_{ii'} \leq 1 - \Lambda_{i'}, \forall i, i' \\ b_{ii'} \geq 1 - \Lambda_i - \Lambda_{i'}, \forall i, i' \end{cases} \quad (37)$$

$$\begin{cases} d_{jj'} \leq \Lambda_j, \forall j, j' \\ d_{jj'} \leq \Lambda_{j'}, \forall j, j' \\ d_{jj'} \geq \Lambda_j + \Lambda_{j'} - 1, \forall j, j' \end{cases} \quad (38)$$

By introducing new auxiliary variables $b_{ij'}$, $d_{jj'}$, $\log(a_{un})$ and R_{ul} are transformed into the concave functions. However, $-\log(I_{un})$ is a convex function with respect to Λ . Therefore, we apply the following proposition to linearize the non-concave part [18].

Proposition 1: Let x be a positive scalar and $f(x) = -(xy) + \log(x) + 1$. We have

$$-\log(y) = \max_{x>0} f(x) \quad (39)$$

and the optimal solution to the right-hand side of (39) is $x = 1/y$. According to Proposition 1, $-\log(I_{un})$ is expressed as

$$-\log(I_{un}) = \max_{x>0} -xI_{un} + \log(x) + 1 \quad (40)$$

so that R_{ul} is given by

$$R_{ul} = \max_{x>0} \sum_{u=1}^U \sum_{n=1}^N (\log(a_{un}) - xI_{un} + \log(x) + 1) \quad (41)$$

For given I_{un} , the optimal x is $x = \frac{1}{I_{un}}$ and for given x , R_{ul} is the concave function of Λ . Therefore, x and Λ can be solved by alternating optimization. In the n -th iteration, R_{ul} is

$$R_{ul} = \sum_{u=1}^U \sum_{n=1}^N (\log(a_{un}) - x^{(n)}I_{un} + \log(x^{(n)}) + 1) \quad (42)$$

where $x^{(n)} = (I_{un}^{(n-1)})^{-1}$. Therefore, in each iteration, the objective $R_{ul} + R_{dl}$ is concave.

Next we tackle the non-convex CRLB constraints in (23a) and (23b). Let $\{\bar{\phi}_{ln}^R, n = 1, \dots, N\}_{l=1}^{\zeta}$ denote the allocation result of sensing subcarriers on ζ transmit APs obtained from supproblem (24). In order to determine the optimal set of transmit APs for given sensing subcarriers allocation, we decompose $\Lambda_j \phi_{jn}^R$ in (23c) into $\sum_{l=1}^{\zeta} \Lambda'_{jl} \cdot \bar{\phi}_{ln}^R$. To clarify more clearly, we represent the above relationship with a matrix expression

$$\begin{bmatrix} \Lambda_1 \phi_{11}^R & \dots & \Lambda_1 \phi_{1N}^R \\ \vdots & \ddots & \vdots \\ \Lambda_J \phi_{J1}^R & \dots & \Lambda_J \phi_{JN}^R \end{bmatrix} = \begin{bmatrix} \Lambda'_{11} & \dots & \Lambda'_{1\zeta} \\ \vdots & \ddots & \vdots \\ \Lambda'_{J1} & \dots & \Lambda'_{J\zeta} \end{bmatrix} \cdot \begin{bmatrix} \bar{\phi}_{11}^R & \dots & \bar{\phi}_{1N}^R \\ \vdots & \ddots & \vdots \\ \bar{\phi}_{\zeta 1}^R & \dots & \bar{\phi}_{\zeta N}^R \end{bmatrix} \quad (43)$$

where each row of subcarriers allocation matrix represents a unique sensing subcarriers allocation pattern and Λ'_{jl} denotes the sensing subcarriers pattern selection factor of the j -th AP. To guarantee the exclusive allocation of each pattern to a single transmit AP, each column of the AP mode selection matrix should satisfy $\sum_{j=1}^J \Lambda'_{jl} = 1$. Meanwhile, each row of the AP mode selection matrix should satisfy $\sum_{l=1}^{\zeta} \Lambda'_{jl} \leq \Lambda_j \zeta$. Then, we introduce the following Lemma, which is easy to prove.

Lemma 1: Suppose that a_{lij} is a real number and B_{lij} is a 2×2 matrix, $l = 1, 2, \dots, \zeta$ and $i, j = 1, 2, \dots, J$. We denote

$\mathbf{a} = [a_{111}, \dots, a_{lij}, \dots, a_{\zeta JJ}]^T$. Then the following equations hold

$$[(\sum_{l=1}^{\zeta} \sum_{i=1}^J \sum_{j=1}^J a_{lij} B_{lij})^{-1}]_{11} = \frac{\mathbf{a}^T \boldsymbol{\omega}_1}{\mathbf{a}^T \mathbf{Q} \mathbf{a}} \quad (44)$$

$$[(\sum_{l=1}^{\zeta} \sum_{i=1}^J \sum_{j=1}^J a_{lij} B_{lij})^{-1}]_{22} = \frac{\mathbf{a}^T \boldsymbol{\omega}_2}{\mathbf{a}^T \mathbf{Q} \mathbf{a}} \quad (45)$$

where $\mathbf{Q}$ is a $\zeta J^2 \times \zeta J^2$ matrix with $[\mathbf{Q}]_{(lij), (l'i'j')} = [B_{lij}]_{11} [B_{l'i'j'}]_{22} - [B_{lij}]_{12} [B_{l'i'j'}]_{21}$, $\boldsymbol{\omega}_1 = [[B_{111}]_{22}, \dots, [B_{lij}]_{22}, \dots, [B_{\zeta JJ}]_{22}]^T$, $\boldsymbol{\omega}_2 = [[B_{111}]_{11}, \dots, [B_{lij}]_{11}, \dots, [B_{\zeta JJ}]_{11}]^T$.

We define $\mathbf{s} = [s_{111}, \dots, s_{lij}, \dots, s_{\zeta JJ}]^T$, where $s_{lij} = \Lambda'_{jl} (1 - \Lambda_i)$ and $\mathbf{B}_{klij}^p = \frac{2}{\sigma^2} \sum_{n=1}^N \sum_{m=1}^M P_R \phi_{ln}^R \mathbf{P}_k(i, j, n, m)$, $\mathbf{B}_{klij}^v = \frac{2}{\sigma^2} \sum_{n=1}^N \sum_{m=1}^M P_R \phi_{ln}^R \mathbf{V}_k(i, j, n, m)$, and according to Lemma 1, the diagonal elements of CRLB matrices $\mathbf{C}_k^p$ and $\mathbf{C}_k^v$ in (21) and (22) can be expressed as

$$[\mathbf{C}_k^p]_{11} = [(\sum_{l=1}^{\zeta} \sum_{i=1}^J \sum_{j=1}^J s_{lij} \mathbf{B}_{klij}^p)^{-1}]_{11} = \frac{\mathbf{s}^T \mathbf{w}_k^{p,1}}{\mathbf{s}^T \mathbf{Q}_k^p \mathbf{s}} \quad (46)$$

$$[\mathbf{C}_k^p]_{22} = [(\sum_{l=1}^{\zeta} \sum_{i=1}^J \sum_{j=1}^J s_{lij} \mathbf{B}_{klij}^p)^{-1}]_{22} = \frac{\mathbf{s}^T \mathbf{w}_k^{p,2}}{\mathbf{s}^T \mathbf{Q}_k^p \mathbf{s}} \quad (47)$$

$$[\mathbf{C}_k^v]_{11} = [(\sum_{l=1}^{\zeta} \sum_{i=1}^J \sum_{j=1}^J s_{lij} \mathbf{B}_{klij}^v)^{-1}]_{11} = \frac{\mathbf{s}^T \mathbf{w}_k^{v,1}}{\mathbf{s}^T \mathbf{Q}_k^v \mathbf{s}} \quad (48)$$

$$[\mathbf{C}_k^v]_{22} = [(\sum_{l=1}^{\zeta} \sum_{i=1}^J \sum_{j=1}^J s_{lij} \mathbf{B}_{klij}^v)^{-1}]_{22} = \frac{\mathbf{s}^T \mathbf{w}_k^{v,2}}{\mathbf{s}^T \mathbf{Q}_k^v \mathbf{s}} \quad (49)$$

where $\mathbf{Q}_k^p$ and $\mathbf{Q}_k^v$ are $\zeta J^2 \times \zeta J^2$ matrices with $[\mathbf{Q}_k^p]_{(klij), (kl'i'j')} = [B_{klij}^p]_{11} [B_{kl'i'j'}^p]_{22} - [B_{klij}^p]_{12} [B_{kl'i'j'}^p]_{21}$, $[\mathbf{Q}_k^v]_{(klij), (kl'i'j')} = [B_{klij}^v]_{11} [B_{kl'i'j'}^v]_{22} - [B_{klij}^v]_{12} [B_{kl'i'j'}^v]_{21}$, $\mathbf{w}_k^{p,1} = [[B_{k111}^p]_{22}, \dots, [B_{klij}^p]_{22}, \dots, [B_{k\zeta JJ}^p]_{22}]^T$, $\mathbf{w}_k^{p,2} = [[B_{k111}^p]_{11}, \dots, [B_{klij}^p]_{11}, \dots, [B_{k\zeta JJ}^p]_{11}]^T$, $\mathbf{w}_k^{v,1} = [[B_{k111}^v]_{22}, \dots, [B_{klij}^v]_{22}, \dots, [B_{k\zeta JJ}^v]_{22}]^T$, $\mathbf{w}_k^{v,2} = [[B_{k111}^v]_{11}, \dots, [B_{klij}^v]_{11}, \dots, [B_{k\zeta JJ}^v]_{11}]^T$. The non-linear equation constraints between $\mathbf{s}$ and Λ can be equivalently transformed into the following inequation constraints

$$\begin{cases} s_{lij} \leq \Lambda'_{jl}, \forall i, j, l \\ s_{lij} \leq 1 - \Lambda_i, \forall i, j, l \\ s_{lij} \geq \Lambda'_{jl} - \Lambda_i, \forall i, j, l \end{cases} \quad (50)$$

Then we convert CRLB constraints in (23a) and (23b) into convex ones by the following steps

$$\frac{\mathbf{s}^T \mathbf{w}}{\mathbf{s}^T \mathbf{Q} \mathbf{s}} \leq \eta \iff -\mathbf{s}^T (\mathbf{Q} + \mathbf{Q}^T) \mathbf{s} + \frac{2}{\eta} \mathbf{s}^T \mathbf{w} \leq 0 \quad (51)$$

We denote $\mathbf{Z} = -(\mathbf{Q} + \mathbf{Q}^T)$ and λ_z as the minimal eigenvalue of $\mathbf{Z}$. Then, (51) is equivalent to

$$\mathbf{s}^T (\mathbf{Z} - \lambda_z \mathbf{I}) \mathbf{s} + \frac{2}{\eta} \mathbf{s}^T \mathbf{w} + \lambda_z \mathbf{s}^T \mathbf{I} \mathbf{s} \leq 0 \quad (52)$$

Since $\mathbf{s}^T \mathbf{I} \mathbf{s} = \sum_{l=1}^{\zeta} \sum_{i=1}^J \sum_{j=1}^J ((1 - \Lambda_i) \Lambda'_{jl})^2 = \zeta(J - \zeta) \triangleq \zeta'$ and $\mathbf{Z} - \lambda_z \mathbf{I}$ is positive semidefinite, (52) is a convex expression.

Based on the above derivations, the problem in (25) is reformulated as

$$\max_{\mathcal{P}_3} R_{ul} + R_{dl} \quad (53)$$

$$\text{s.t.} \quad \sum_{j=1}^J \Lambda_j = \zeta \quad (53a)$$

$$\sum_{j=1}^J \Lambda'_{jl} = 1, \forall l \quad (53b)$$

$$\sum_{l=1}^{\zeta} \Lambda'_{jl} \leq \Lambda_j \zeta, \forall j \quad (53c)$$

$$\mathbf{s}^T (\mathbf{Z}_k^p - \lambda_{z_k} \mathbf{I}) \mathbf{s} + \frac{2}{\eta_p} \mathbf{s}^T \mathbf{w}_k^{p,1} + \lambda_{z_k} \zeta' \leq 0, \forall k \quad (53d)$$

$$\mathbf{s}^T (\mathbf{Z}_k^p - \lambda_{z_k} \mathbf{I}) \mathbf{s} + \frac{2}{\eta_p} \mathbf{s}^T \mathbf{w}_k^{p,2} + \lambda_{z_k} \zeta' \leq 0, \forall k \quad (53e)$$

$$\mathbf{s}^T (\mathbf{Z}_k^v - \lambda_{z_k} \mathbf{I}) \mathbf{s} + \frac{2}{\eta_v} \mathbf{s}^T \mathbf{w}_k^{v,1} + \lambda_{z_k} \zeta' \leq 0, \forall k \quad (53f)$$

$$\mathbf{s}^T (\mathbf{Z}_k^v - \lambda_{z_k} \mathbf{I}) \mathbf{s} + \frac{2}{\eta_v} \mathbf{s}^T \mathbf{w}_k^{v,2} + \lambda_{z_k} \zeta' \leq 0, \forall k \quad (53g)$$

$$(37), (38), (50) \quad (53h)$$

where $\mathcal{P}_3 \triangleq \{\mathbf{\Lambda}, \mathbf{\Lambda}', \mathbf{s}, \{b_{ii'}\}_{i=1, i'=1}^{J,J} \in \{0, 1\}, \{d_{jj'}\}_{j=1, j'=1}^{J,J} \in \{0, 1\}\}$ and $\mathbf{\Lambda}' = [\Lambda'_{11}, \dots, \Lambda'_{j1}, \dots, \Lambda'_{J\zeta}]$, R_{ul} and R_{dl} are defined in (42) and (36) respectively. For given ζ , (53) is a convex quadratic integer problem, which can be efficiently solved by optimization tools such as Mosek. We outline the algorithm for solving the subproblem (53) in Algorithm 2.

Algorithm 2 Algorithm for Solving Problem in (53)

- 1: Set the convergence tolerance $\Delta = 10^{-5}$, the iteration counter $n = 1$, and initialize $\mathbf{\Lambda}^{(0)}$, ζ .
- 2: **Repeat:**
 - (S1) Update $x^{(n)}$ by $x^{(n)} = (I_{un}^{(n-1)})^{-1}$;
 - (S2) For given $x^{(n)}$ solve problem (53) to obtain the optimal solution $\mathcal{P}_3^{(n)}$ and objective $(R_{dl} + R_{ul})_{\zeta}^{(n)}$, calculate $(I_{un}^{(n)})^{-1}$;
 - (S3) $n = n + 1$.
- 3: **Until** $|(R_{dl} + R_{ul})_{\zeta}^{(n)} - (R_{dl} + R_{ul})_{\zeta}^{(n-1)}| < \Delta$.
- 4: **Output:** the optimal solution $\mathbf{\Lambda}^* = \arg \max_{\zeta} (R_{dl} + R_{ul})_{\zeta}$.

Computational Complexity: The computation complexity of AO optimization for solving problem (23) depends on the complexity of Algorithm 1 and Algorithm 2. For Algorithm 1, the computation complexity is dominated by solving SDP problems in (24). In the CVX toolbox, the SDP is solved by the standard interior-point method (IPM), whose complexity consists of iteration complexity $\sqrt{\beta(K)} \cdot \ln(1/\epsilon)$ and per-iteration

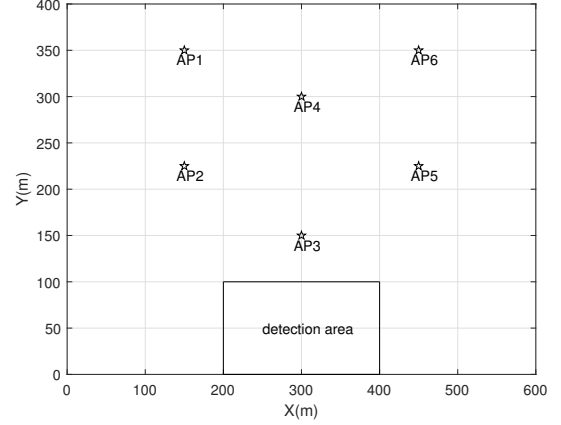


Fig. 2: Locations of APs and detection area.

TABLE I: The Simulation Parameters

Parameter	Quantity	Parameter	Quantity	Parameter	Quantity
P_{max}	3, 5, 7W	Δf	15KHz	U	3
N_D	32	N	32, 24	$\sigma_{dl}^2, \sigma_{ul}^2$	-120dBm
J	5, 6, 7	M	16	σ_r^2	-130dBm
f_c	3GHz	Q	3	K	2

computation cost C . The total complexity is on the order of $\sqrt{\beta(K)} \cdot \ln(1/\epsilon) \cdot C$ [19] where $\epsilon > 0$ is a constant. In Algorithm 1, $\sqrt{\beta(K)} = \sqrt{8K + N + 3}$, $C = N \cdot 32K + N^2 \cdot 16K + 2N + 6 + N^3$. The computation complexity of the SDP problem is about $\mathcal{O}(\sqrt{8K + N + 3}N^3)$. Therefore, the computation complexity of Algorithm 1 is $\mathcal{O}(\sqrt{8K + N + 3}N^3N_{c1})$, where N_{c1} is the iteration number of Algorithm 1. For algorithm 2, the computation complexity is dominated by solving convex quadratic integer problem in (53). In the Mosek, the convex quadratic integer problem can be solved by SDP-based branch-and-bound (BB) method¹, whose complexity in our proposed algorithm is $\mathcal{O}(\sqrt{9J^2 + 12K + 2\zeta J^3}N_{BB})$. Therefore, the computation complexity of Algorithm 2 is $\mathcal{O}((\sqrt{9J^2 + 12K + 2\zeta J^3}N_{BB}N_{c2}))$, where N_{BB} is the number of main node-processing loop of BB algorithm and N_{c2} is the iteration number of Algorithm 2. Assume the iteration number of AO is N_{AO} . The overall complexity of solving (23) is $\mathcal{O}((\sqrt{9J^2 + 12K + 2\zeta J^3}N_{BB}N_{c2} + \sqrt{8K + N + 3}N^3N_{c1})N_{AO})$.

V. NUMERICAL RESULTS

In this section, we present some numerical results to evaluate the performance of the proposed algorithm. The simulation parameters are detailed in Table I. In the system configuration, 6 APs are evenly distributed within the area depicted in Fig. 2. We assume that there are two targets in the detection area, and three UL-UEs and three DL-UEs in the whole area. In each experiment, the locations of targets (in the detection

¹Source codes of SDP-based BB method applied by Mosek are provided in the website <https://nbviewer.org/github/MOSEK/Tutorials/blob/master/binary-quadratic/binquad.ipynb>.

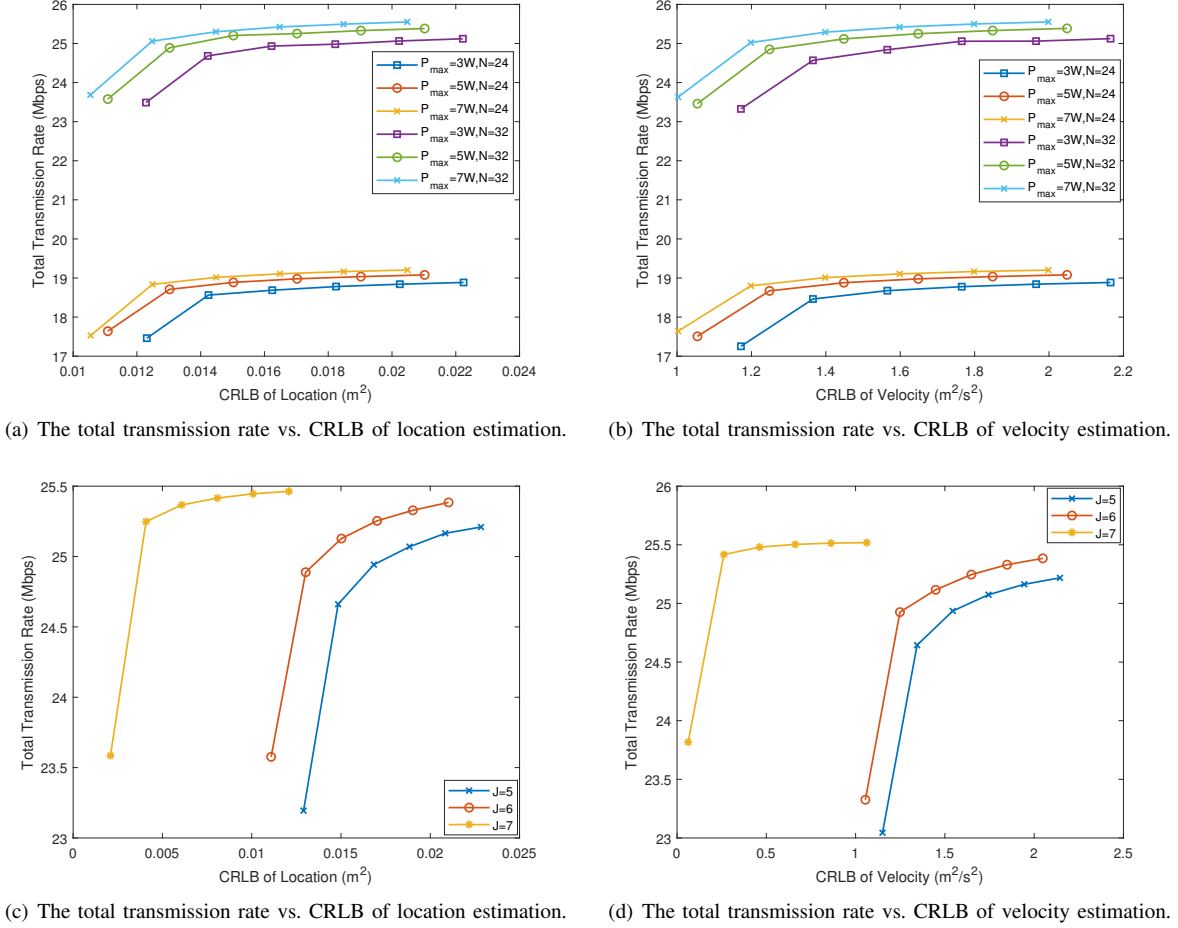


Fig. 3: The tradeoff between the total transmission rate and CRLB with different parameters.

area) and UEs are randomly generated. In the channel model, elements in ϵ_{jaq} and ϵ_{uai} are independent and identically distributed Gaussian variables with zero mean and variables $\sigma_{\epsilon_{jaq}}^2$, $\sigma_{\epsilon_{uai}}^2$ and RCS_{jki} s are random values in $[0.06, 0.1]$. For different multipath components, we set $\sum_{a=1}^{A_0} \sigma_{\epsilon_{jaq}}^2 = 0.1$ and $\sum_{a=1}^{A_1} \sigma_{\epsilon_{uai}}^2 = 0.1$. The transmission rates and CRLBs are obtained by averaging experiments with Monte Carlo method.

A. The tradeoff between communication and sensing performance with different parameters

In this subsection, we illustrate the impact of various parameters on the tradeoff between communication and sensing performance by solving problem (23).

Specifically, in each experiment, for given estimation accuracy constraints η_p and η_v , we solve (23) to obtain the optimal subcarrier/power allocation and APs mode selection scheme. Subsequently, we compute the transmission rate $(R_{dl} + R_{ul})/T$ and CRLBs of location and velocity estimations based on (21) and (22), respectively. Multiple experiments are implemented to calculate the average transmission rates and CRLBs. By varying η_p (m²) or η_v (m²/s²), the tradeoff performance between the average transmission rate and CRLBs of location and velocity estimations with different N and P_{max} are

presented in Fig. 3(a) and 3(b). We set $J = 6$, $\zeta = 2$ and adopt ZF receiver in UL of communication. It can be observed that increasing P_{max} will decrease CRLB of location/velocity estimation and increase the total transmission rate simultaneously. However, as N increases, the CRLBs of location and velocity estimation are not improved significantly. This is because the location estimation depends more on antennas number N_D according to (64)-(67) and elements of V_k are independent of N according to (68)-(71).

The tradeoff performance between the total transmission rate and CRLBs of location and velocity estimations with varying number of APs J are given in Fig. 3(c) and 3(d) (AP7 is located in (150m, 75m)). We set $N = 32$ and $P_{max} = 5W$. When $J = 6$, AP1-AP6 in Fig. 2 are employed when $J = 6$ and AP1-AP5 in Fig. 2 are employed when $J = 5$. It can be seen that when bandwidth and transmit power are fixed, increasing the number of APs is an effective method to improve the tradeoff performance between communication and sensing. From equation (61), we can observe that Λ_j has a comparable influence on FIM as P_R . However, increasing J makes more contribution to the CRLB, due to the absence of summation term ‘ $\sum$ ’ associated with P_R .

Fig. 4 illustrates the CRLB of location estimation with different inter-APs interference power σ_I^2 . In this case, we

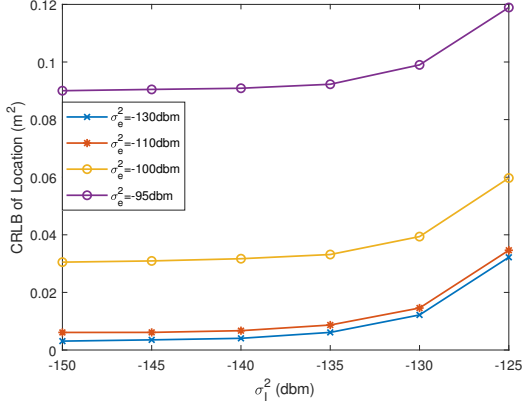


Fig. 4: The CRLB of location estimation vs. inter-APs interference power σ_I^2 with different UL interference power σ_e^2 .

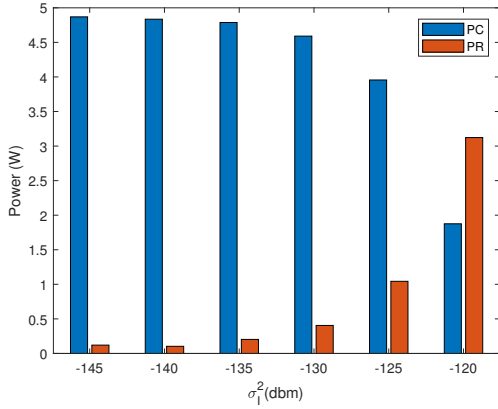


Fig. 5: Power allocation for communication and sensing with different σ_I^2 .

set $J = 6, P_{max} = 5W, N = 32$. For each σ_I^2 , we decrease the value of η_p until the problem (23) becomes unfeasible. Then, the minimized η_p which ensures (23) feasible is utilized to calculate the CRLB of location estimation. Therefore, the CRLB in Fig. 4 is the lowest achievable CRLB of location estimation for given parameters. Obviously, the perception performance will deteriorate with the increase of σ_I^2 . Moreover, it is observed that the impact of σ_I^2 or σ_e^2 on CRLB is nonlinear. When σ_I^2 or σ_e^2 exceeds a certain value, estimation performance will suffer from serious decline. This is attributed to the limited resources allocated for detection. From (21) and (22), it is evident that when the expression following ' $\frac{2}{\sigma_x^2}$ ' reaches the maximum value, the further increase of σ^2 will lead to a substantial reduction in the CRLB.

Fig. 5 presents the power allocation schemes with different σ_I^2 , where 'PC' and 'PR' stand for the total DL transmit power allocated to communication and sensing respectively. We set $\eta_p = 0.08$ and then solve problem (23) to calculate the total power allocated to communication and sensing respectively, with varying σ_I^2 . From Fig. 5, we can observe that the increasing of σ_I^2 has a serious impact on sensing performance so that when $\sigma_I^2 \geq -120dBm$, most resources

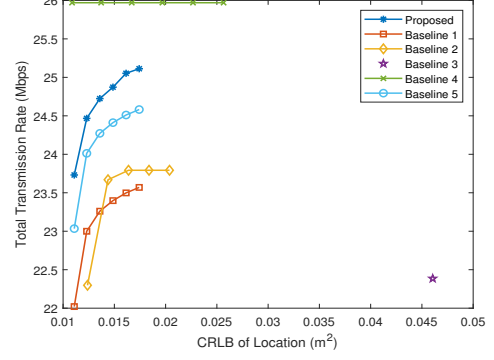


Fig. 6: The tradeoff between the total transmission rate and CRLB of location with different optimization schemes.

will be used for perception. It is intuitive that as interference power increases, more power will be allocated for sensing to satisfy the accuracy requirements.

B. Comparison of different optimization schemes

In order to intuitively illustrate the performance of the proposed scheme, we consider the following schemes for comparison.

- *Baseline 1*: Power/subcarrier allocation is optimized by solving problem in (24) and APs mode selection is fixed.
- *Baseline 2*: Power/subcarrier allocation is fixed and APs mode selection is optimized by solving (25).
- *Baseline 3*: Both power/subcarrier allocation and APs mode selection are predetermined and aren't optimized.
- *Baseline 4*: Both power/subcarrier allocation and APs mode selection are jointly optimized by solving (23) without CRLBs constraints, which means the optimal total transmission rate in this scheme is the upper bound of that of the proposed scheme.
- *Baseline 5*: Both power/subcarrier allocation and APs mode selection are jointly optimized in the scenario where UL communication does not occupy the bandwidth allocated for perception.

Fig. 6 illustrates the tradeoff performance between the average transmission rate and CRLB of location estimation with different resource allocation schemes. We set $J = 6, N = 32, P_{max} = 5W, \sigma_I^2 = -130dBm, \sigma_e^2 = -135dBm$. It can be seen in Fig. 6, the *Proposed* scheme achieves the best tradeoff performance by jointly optimizing the power/subcarrier allocation and the APs mode selection, compared to *Baseline 1-3,5*. As CRLB increases, the total transmission rate of *Proposed* scheme gradually approaches the upper bound of the rate in *Baseline 4*. Additionally, the performance gap between the *Proposed* scheme and *Baseline 1* reveals that the optimization of APs mode selection can efficiently enhance the tradeoff performance. In *Baseline 2*, the tradeoff performance consists of five discrete points due to the fact that the optimization of APs mode selection in (25) is a discrete optimization problem, and the optimization results will not continuously change with the change of η_p . It means that only when there is a significant change in η_p , the solution of (25) and corresponding

TABLE II: The simulation parameters of different network design schemes.

CS-A	$\sigma_I^2 = -130dBm$	$R = 2$	$\frac{B_{DL}}{B_{UL}} = 1$
CS-B	$\sigma_I^2 = -130dBm$	$R = 3$	$\frac{B_{DL}}{B_{UL}} = 1$
CS-C	$\sigma_I^2 = -135dBm$	$R = 2$	$\frac{B_{DL}}{B_{UL}} = 3$
PS-A	$\sigma_I^2 = -130dBm$	$\sigma_e^2 = -110dBm$	
PS-B	$\sigma_I^2 = -130dBm$	$\sigma_e^2 = -130dBm$	
PS-C	$\sigma_I^2 = -135dBm$	$\sigma_e^2 = -130dBm$	

transmission rate and CRLB will change. When both the power/subcarrier allocation and mode selection of APs are fixed (*Baseline 3*), the tradeoff performance is a discrete point (0.045,22.4). In *Baseline 5*, echo signals are not interfered by UL communication signals, at the cost of reduced UL bandwidth, which is better than other Baselines but falls short of the proposed scheme.

C. Comparison with different ISAC design schemes

In this subsection, we evaluate an existing ISAC network design schemes for comparison. In the compared scheme (CS), the ISAC system consists of coordinated communication BSs and dedicated radar receivers under the control of a CPU [10]. Table II provides some parameters of this scheme, where R is the number of radar transmitters. $\frac{B_{DL}}{B_{UL}}$ is the bandwidth allocation ratio of DL and UL. For a fair comparison, in all schemes, we set $J = 6$, $N_D = 32$, $N = 32$, $P_{max} = 5W$, $K = 2$. In the CS, each BS uses one antenna for omnidirectional transmission and DL communication signals are also used for detection. Moreover, each BS operates in frequency division duplex (FDD) mode so that UL is not interfered by DL.

In the CS, R BSs are utilized for transmission and $6 - R$ radar receivers collaborate to detect the targets. Each BS utilizes $N_D - 1$ antennas to receive UL communication signals and R BSs collaborate to serve communication users under the control of a CPU. We derive the CRLB of location estimation as radar performance metric as well as signal-to-noise ratio (SNR) of DL communication as communication performance metric and optimize the transmit power of each BS with the method in [10]. Compared to the proposed scheme (PS), the advantages of the CS are that the radar receiver is not interfered by UL communication signals and the UL communication signals are also not interfered by DL communication signals. From Fig. 7, we can observe that

- Decreasing R or σ_I^2 or increasing $\frac{B_{DL}}{B_{UL}}$ can improve the sensing performance of the CS. The transmission rate of the CS is much lower than that of PS because the CS didn't use transmit beamforming and optimal resource allocation. Compared with the PS, CS uses the same signals to communicate and detect so that there is no obvious tradeoff between the total transmission rate and CRLB.
- From PS-(A-C), we can observe that decreasing σ_I^2 has more improvement than decreasing σ_e^2 . This is because the interference from BSs is larger than that from uplink users. Comparing PS-(A-C) with CS-(A-C), we can see

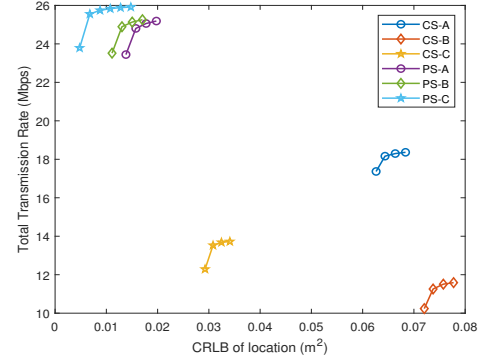


Fig. 7: Tradeoff performances of proposed scheme and CS.

that the tradeoff performance of PS is better than CS, and the maximum total transmission rate of PS is about 36% higher than that of the CS.

VI. CONCLUSION

In this paper, we design a DTDD-enabled ISAC system, which leverages the OFDM-based dual-function waveform as transmit signals. In order to flexibly support communication between diverse users and perception of specific region while enhancing the spectrum efficiency, we adopt frequency division mode in DL transmission to achieve simultaneous communication and perception, while allowing UL and DL communication to share the same frequency bands. We reduce interference and improve the tradeoff performance between communication and sensing by reasonably configuring APs operation modes and optimizing resource allocation. Given the complexity of finding the global optimum for the MINLP problem, we employ an AO method to decompose the problem into two subproblems, which are efficiently solved using the PCCP method and convex quadratic integer programming, respectively. Simulation results highlight the impact of various parameters on the tradeoff between communication and sensing performance and demonstrate the superiority of our design over existing ISAC schemes in scenarios where inter-AP and UL interference are effectively suppressed. Considering the practical scenario where the links between APs and targets are blocked, an interesting extension is to combine our proposed method with the reconfigurable intelligent surface (RIS) [20]-[21] by further optimizing the coding and deployment of RIS.

APPENDIX THE DERIVATION OF $F(\mathbf{u})$

In this part, we will provide the detailed derivation of $F(\mathbf{u})$ as follows. Firstly, $\frac{\partial \mu}{\partial \gamma}$ in (15) can be expressed as $\frac{\partial \mu}{\partial \gamma} =$

$[\frac{\partial \mu_1^T}{\partial \gamma}, \dots, \frac{\partial \mu_j^T}{\partial \gamma}, \dots, \frac{\partial \mu_L^T}{\partial \gamma}]^T$, where

$$\frac{\partial \mu_j}{\partial \gamma} = \begin{bmatrix} \frac{\partial \mu_{j111}}{\partial \varphi_1} & \frac{\partial \mu_{j111}}{\partial \varphi_2} & \dots & \frac{\partial \mu_{j111}}{\partial \varphi_K} & \frac{\partial \mu_{j111}}{\partial c} \\ \vdots & \vdots & \dots & \vdots & \vdots \\ \frac{\partial \mu_{j1mn}}{\partial \varphi_1} & \frac{\partial \mu_{j1mn}}{\partial \varphi_2} & \dots & \frac{\partial \mu_{j1mn}}{\partial \varphi_K} & \frac{\partial \mu_{j1mn}}{\partial c} \\ \vdots & \vdots & \dots & \vdots & \vdots \\ \frac{\partial \mu_{jJMN}}{\partial \varphi_1} & \frac{\partial \mu_{jJMN}}{\partial \varphi_2} & \dots & \frac{\partial \mu_{jJMN}}{\partial \varphi_K} & \frac{\partial \mu_{jJMN}}{\partial c} \end{bmatrix} \quad (54)$$

where

$$\frac{\partial \mu_{j1mn}}{\partial \varphi_k} = [0, \dots, \frac{\partial \mu_{j1mn}}{\partial \varphi_{jki}}, \dots, 0] \quad (55)$$

where

$$\frac{\partial \mu_{j1mn}}{\partial \varphi_{jki}} = [\frac{\partial \mu_{j1mn}}{\partial \tau_{jki}}, \frac{\partial \mu_{j1mn}}{\partial f_{jki}}, \frac{\partial \mu_{j1mn}}{\partial \alpha_{ik}}, \frac{\partial \mu_{j1mn}}{\partial \beta_{kj}}] \quad (56)$$

where

$$\begin{aligned} \frac{\partial \mu_{j1mn}}{\partial \tau_{jki}} &= (1 - \Lambda_i)(-j2\pi n \Delta f \Lambda_j c_{jki} \sqrt{P_R} \phi_{jn}^R e^{j2\pi m T f_{jki}} \\ &\quad e^{-j2\pi n \Delta f \tau_{jki}} \mathbf{a}_r(\alpha_{ik}) \mathbf{a}_t^T(\beta_{kj}) \boldsymbol{\omega}_{jn}^R b_{jmn}^R) \triangleq \boldsymbol{\mu}_\tau \\ \frac{\partial \mu_{j1mn}}{\partial f_{jki}} &= (1 - \Lambda_i)(j2\pi m T \Lambda_j c_{jki} \sqrt{P_R} \phi_{jn}^R e^{j2\pi m T f_{jki}} \\ &\quad e^{-j2\pi n \Delta f \tau_{jki}} \mathbf{a}_r(\alpha_{ik}) \mathbf{a}_t^T(\beta_{kj}) \boldsymbol{\omega}_{jn}^R b_{jmn}^R) \triangleq \boldsymbol{\mu}_f \\ \frac{\partial \mu_{j1mn}}{\partial \alpha_{ik}} &= (1 - \Lambda_i)(-j \frac{2\pi}{\lambda_n} d \cos \alpha_{ik} \Lambda_j c_{jki} \sqrt{P_R} \phi_{jn}^R \\ &\quad e^{j2\pi m T f_{jki}} e^{-j2\pi n \Delta f \tau_{jki}} \mathbf{a}_d \cdot \mathbf{a}_r(\alpha_{ik}) \mathbf{a}_t^T(\beta_{kj}) \\ &\quad \boldsymbol{\omega}_{jn}^R b_{jmn}^R) \triangleq \boldsymbol{\mu}_\alpha \\ \frac{\partial \mu_{j1mn}}{\partial \beta_{kj}} &= (1 - \Lambda_i)(-j \frac{2\pi}{\lambda_n} d \cos \beta_{kj} \Lambda_j c_{jki} \sqrt{P_R} \phi_{jn}^R \\ &\quad e^{j2\pi m T f_{jki}} e^{-j2\pi n \Delta f \tau_{jki}} \mathbf{a}_d \cdot \mathbf{a}_r(\alpha_{ik}) \mathbf{a}_t^T(\beta_{kj}) \\ &\quad \boldsymbol{\omega}_{jn}^R b_{jmn}^R) \triangleq \boldsymbol{\mu}_\beta \end{aligned} \quad (57)$$

where $\mathbf{a}_d = [0, 1, \dots, N_D - 1]^T$. Ignore interference between targets and items related to $\partial \mathbf{u} / \partial c$, $\mathbf{F}(\gamma)$ in (15) becomes the block diagonal matrix below

$$\mathbf{F}(\gamma) = \begin{bmatrix} \mathbf{F}_1(\gamma) & \mathbf{0} & \dots & \mathbf{0} \\ \mathbf{0} & \mathbf{F}_2(\gamma) & \dots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \dots & \mathbf{F}_K(\gamma) \end{bmatrix} \quad (58)$$

where $\mathbf{F}_k(\gamma)$ is the $4J^2 \times 4J^2$ submatrix corresponding to the k -th target and has the following form

$$\begin{aligned} \mathbf{F}_k(\gamma) &= \frac{2}{\sigma^2} \text{Re} \left(\sum_{i=1}^J \sum_{j=1}^J \sum_{n=1}^N \sum_{m=1}^M \frac{\partial^H \mu_{j1mn}}{\partial \varphi_k} \frac{\partial \mu_{j1mn}}{\partial \varphi_k} \right) \\ &= \frac{2}{\sigma^2} \text{Re} \left(\sum_{m,n=1}^{M,N} \begin{bmatrix} \mathbf{A}_{1k1}^{mn} & \dots & \mathbf{0} & \dots & \mathbf{0} \\ \vdots & \ddots & \vdots & \dots & \vdots \\ \mathbf{0} & \dots & \mathbf{A}_{jki}^{mn} & \dots & \mathbf{0} \\ \vdots & \dots & \vdots & \ddots & \vdots \\ \mathbf{0} & \dots & \mathbf{0} & \dots & \mathbf{A}_{JkJ}^{mn} \end{bmatrix} \right) \end{aligned} \quad (59)$$

where $\mathbf{A}_{jki}^{mn} = \frac{\partial^H \mu_{j1mn}}{\partial \varphi_{jki}} \frac{\partial \mu_{j1mn}}{\partial \varphi_{jki}}$. According to (55)-(57), a more specific form of $\mathbf{A}_{jki}^{mn}$ is given below

$$\mathbf{A}_{jki}^{mn} = \begin{bmatrix} \boldsymbol{\mu}_\tau^H \boldsymbol{\mu}_\tau & \boldsymbol{\mu}_\tau^H \boldsymbol{\mu}_f & \boldsymbol{\mu}_\tau^H \boldsymbol{\mu}_\alpha & \boldsymbol{\mu}_\tau^H \boldsymbol{\mu}_\beta \\ \boldsymbol{\mu}_f^H \boldsymbol{\mu}_\tau & \boldsymbol{\mu}_f^H \boldsymbol{\mu}_f & \boldsymbol{\mu}_f^H \boldsymbol{\mu}_\alpha & \boldsymbol{\mu}_f^H \boldsymbol{\mu}_\beta \\ \boldsymbol{\mu}_\alpha^H \boldsymbol{\mu}_\tau & \boldsymbol{\mu}_\alpha^H \boldsymbol{\mu}_f & \boldsymbol{\mu}_\alpha^H \boldsymbol{\mu}_\alpha & \boldsymbol{\mu}_\alpha^H \boldsymbol{\mu}_\beta \\ \boldsymbol{\mu}_\beta^H \boldsymbol{\mu}_\tau & \boldsymbol{\mu}_\beta^H \boldsymbol{\mu}_f & \boldsymbol{\mu}_\beta^H \boldsymbol{\mu}_\alpha & \boldsymbol{\mu}_\beta^H \boldsymbol{\mu}_\beta \end{bmatrix} \quad (60)$$

We denote $\mathbf{A}_{jki}^{mn}$ as $\mathbf{A}_{jki}^{mn} = \Lambda_j(1 - \Lambda_i) P_R \phi_{jn}^R \tilde{\mathbf{A}}_{jki}^{mn}$. According to the chain rule in (16), $\mathbf{F}(\mathbf{u})$ is a block diagonal matrix and the k -th diagonal block $\mathbf{F}_k(\mathbf{u})$ is

$$\mathbf{F}_k(\mathbf{u}) = \frac{2}{\sigma^2} \sum_{i=1}^J \sum_{j=1}^J \sum_{n=1}^N \sum_{m=1}^M \Lambda_j(1 - \Lambda_i) P_R \phi_{jn}^R \mathbf{J}_{jki} \tilde{\mathbf{A}}_{jki}^{mn} \mathbf{J}_{jki}^T \quad (61)$$

The inverse matrix of $\mathbf{F}_k(\mathbf{u})$ is the CRLB matrix of the k -th target. To obtain an analytical form of CRLB, we further ignore the coupling between position and velocity estimation. Then $\mathbf{F}_k(\mathbf{u})$ is simplified as a block diagonal matrix and we can obtain the lower bound of CRLB by inverting the block diagonal matrix. The block diagonal matrix form of $\mathbf{F}_k(\mathbf{u})$ is

$$\mathbf{F}_k(\mathbf{u}) = \frac{2}{\sigma^2} \sum_{i=1}^J \sum_{j=1}^J \sum_{n=1}^N \sum_{m=1}^M \Lambda_j(1 - \Lambda_i) P_R \phi_{jn}^R \boldsymbol{\Psi}_k \quad (62)$$

where $\boldsymbol{\Psi}_k$ is a 4×4 matrix with the following form

$$\boldsymbol{\Psi}_k(i, j, n, m) = \begin{bmatrix} \mathbf{P}_k(i, j, n, m) & \mathbf{0} \\ \mathbf{0} & \mathbf{V}_k(i, j, n, m) \end{bmatrix} \quad (63)$$

Both $\mathbf{P}_k(i, j, n, m)$ and $\mathbf{V}_k(i, j, n, m)$ are 2×2 matrices and given as follows,

$$[\mathbf{P}_k]_{1,1} = \mathbf{J}_{jki}(1, :) \tilde{\mathbf{A}}_{jki}^{mn} \mathbf{J}_{jki}^T(:, 1) \quad (64)$$

$$[\mathbf{P}_k]_{1,2} = \mathbf{J}_{jki}(1, :) \tilde{\mathbf{A}}_{jki}^{mn} \mathbf{J}_{jki}^T(:, 2) \quad (65)$$

$$[\mathbf{P}_k]_{2,1} = \mathbf{J}_{jki}(2, :) \tilde{\mathbf{A}}_{jki}^{mn} \mathbf{J}_{jki}^T(:, 1) \quad (66)$$

$$[\mathbf{P}_k]_{2,2} = \mathbf{J}_{jki}(2, :) \tilde{\mathbf{A}}_{jki}^{mn} \mathbf{J}_{jki}^T(:, 2) \quad (67)$$

$$[\mathbf{V}_k]_{1,1} = \mathbf{J}_{jki}(3, :) \tilde{\mathbf{A}}_{jki}^{mn} \mathbf{J}_{jki}^T(:, 3) \quad (68)$$

$$[\mathbf{V}_k]_{1,2} = \mathbf{J}_{jki}(3, :) \tilde{\mathbf{A}}_{jki}^{mn} \mathbf{J}_{jki}^T(:, 4) \quad (69)$$

$$[\mathbf{V}_k]_{2,1} = \mathbf{J}_{jki}(4, :) \tilde{\mathbf{A}}_{jki}^{mn} \mathbf{J}_{jki}^T(:, 3) \quad (70)$$

$$[\mathbf{V}_k]_{2,2} = \mathbf{J}_{jki}(4, :) \tilde{\mathbf{A}}_{jki}^{mn} \mathbf{J}_{jki}^T(:, 4) \quad (71)$$

REFERENCES

- [1] Z. Wang, K. Han, J. Jiang, Z. Wei, G. Zhu, Z. Feng, J. Lu, and C. Meng, "Symbiotic Sensing and Communications Towards 6G: Vision, Applications, and Technology Trends," in *2021 IEEE 94th Vehicular Technology Conference (VTC2021-Fall)*, pp. 1–5, 2021.
- [2] J. Li and P. Stoica, "MIMO Radar with Collocated Antennas," *IEEE Signal Processing Magazine*, vol. 24, no. 5, pp. 106–114, 2007.
- [3] P. Stoica, J. Li, and Y. Xie, "On Probing Signal Design For MIMO Radar," *IEEE Transactions on Signal Processing*, vol. 55, no. 8, pp. 4151–4161, 2007.
- [4] F. Liu, C. Masouros, A. Li, H. Sun, and L. Hanzo, "MU-MIMO Communications With MIMO Radar: From Co-Existence to Joint Transmission," *IEEE Transactions on Wireless Communications*, vol. 17, no. 4, pp. 2755–2770, 2018.

- [5] H. Hua, J. Xu, and T. X. Han, "Optimal Transmit Beamforming for Integrated Sensing and Communication," *IEEE Transactions on Vehicular Technology*, pp. 1–16, 2023.
- [6] A. Sabharwal, P. Schniter, D. Guo, D. W. Bliss, S. Rangarajan, and R. Wichman, "In-Band Full-Duplex Wireless: Challenges and Opportunities," *IEEE Journal on Selected Areas in Communications*, vol. 32, no. 9, pp. 1637–1652, 2014.
- [7] K. E. Kolodziej, B. T. Perry, and J. S. Herd, "In-Band Full-Duplex Technology: Techniques and Systems Survey," *IEEE Transactions on Microwave Theory and Techniques*, vol. 67, no. 7, pp. 3025–3041, 2019.
- [8] M. L. Rahman, J. A. Zhang, X. Huang, Y. J. Guo, and R. W. Heath, "Framework for a Perceptive Mobile Network Using Joint Communication and Radar Sensing," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 56, no. 3, pp. 1926–1941, 2020.
- [9] A. Zhang, M. L. Rahman, X. Huang, Y. J. Guo, S. Chen, and R. W. Heath, "Perceptive Mobile Networks: Cellular Networks With Radio Vision via Joint Communication and Radar Sensing," *IEEE Vehicular Technology Magazine*, vol. 16, no. 2, pp. 20–30, 2021.
- [10] Y. Huang, Y. Fang, X. Li, and J. Xu, "Coordinated Power Control for Network Integrated Sensing and Communication," *IEEE Transactions on Vehicular Technology*, vol. 71, no. 12, pp. 13361–13365, 2022.
- [11] D. Wang, M. Wang, P. Zhu, J. Li, J. Wang, and X. You, "Performance of Network-Assisted Full-Duplex for Cell-Free Massive MIMO," *IEEE Transactions on Communications*, vol. 68, no. 3, pp. 1464–1478, 2020.
- [12] A. K. Gupta, M. N. Kulkarni, E. Visotsky, F. W. Vook, A. Ghosh, J. G. Andrews, and R. W. Heath, "Rate Analysis and Feasibility of Dynamic TDD in 5G Cellular Systems," in *2016 IEEE International Conference on Communications (ICC)*, pp. 1–6, 2016.
- [13] F. Zeng, J. Yu, J. Li, F. Liu, D. Wang, and X. You, "Integrated sensing and communication for network-assisted full-duplex cell-free distributed massive mimo systems," *ArXiv*, vol. abs/2311.05101, 2023.
- [14] Z. Yu, H. Ren, C. Pan, G. Zhou, R. Wang, M. Liu, and J. Wang, "Addressing the mutual interference in uplink isac receivers: A projection method," *IEEE Wireless Communications Letters*, vol. 13, no. 11, pp. 3109–3113, 2024.
- [15] Z. quan Luo, W. k. Ma, A. M.-C. So, Y. Ye, and S. Zhang, "Semidefinite Relaxation of Quadratic Optimization Problems," *IEEE Signal Processing Magazine*, vol. 5, pp. 20–34, 2010.
- [16] C. Zhong, M. Lou, C. Gu, L. Tang, and Y. Bai, "Performance Optimization and Parameters Estimation for MIMO-OFDM Dual-functional Communication-radar Systems," *Digital Communications and Networks*, 2023.
- [17] Q.-D. Vu, K.-G. Nguyen, and M. Juntti, "Max-Min Fairness for Multicast Multigroup Multicell Transmission under Backhaul Constraints," in *2016 IEEE Global Communications Conference (GLOBECOM)*, pp. 1–6, 2016.
- [18] R. Feng, Q. Li, Q. Zhang, and J. Qin, "Robust Secure Beamforming in MISO Full-Duplex Two-Way Secure Communications," *IEEE Transactions on Vehicular Technology*, vol. 65, no. 1, pp. 408–414, 2016.
- [19] K. Y. Wang, M. C. So, T. H. Chang, W. K. Ma, and C. Y. Chi, "Outage Constrained Robust Transmit Optimization for Multiuser MISO Downlinks: Tractable Approximations by Conic Optimization," *IEEE Transactions on Signal Processing*, vol. 62, 2014.
- [20] K. Zhi, C. Pan, H. Ren, and K. Wang, "Power scaling law analysis and phase shift optimization of ris-aided massive mimo systems with statistical csi," *IEEE Transactions on Communications*, vol. 70, no. 5, pp. 3558–3574, 2022.
- [21] T. Wu, C. Pan, K. Zhi, H. Ren, M. El-kashlan, C.-X. Wang, R. Schober, and X.-H. You, "Exploit high-dimensional ris information to localization: What is the impact of faulty element?," *IEEE Journal on Selected Areas in Communications*, vol. 42, no. 10, pp. 2803–2819, 2024.



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