# Integrated Sensing, Communications, and Powering for Statistical-QoS Provisioning Over Next-Generation Massive-MIMO Mobile Networks

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***Abstract*—The *integrated sensing and communication (ISAC)* has been proposed as a key technique to support the next generation traffic with stringent quality-of-service (QoS) requirements through sensing and communicating using the same radio frequency and hardware. *Simultaneous wireless information and power transfer (SWIPT)* has also emerged to simultaneously deliver information and energy to a receiver. However, how to integrate ISAC with SWIPT to support the stringent QoS traffic has imposed many new challenges not encountered before. To overcome these challenges, in this paper we propose an *integrated sensing, communications, and powering* (ISACP) technique for supporting both sensing and communication QoS provisioning while delivering the power over the next-generation wireless networks using massive multiple-input and multiple-output (massive MIMO) communications. First, we develop the system models for the ISACP scheme to simultaneously sense the targeted mobile users (MUs), transmit the information, and deliver the power. Second, we propose a hypothesis testing based scheme to estimate the MU's angle-of-arrival using the sensing signal. Third, we employ the *Cramér-Rao bound* (CRB) to measure the performance of sensing and maximize the energy-efficiency with satisfying requirements of both sensing and communication performances. Finally, we use numerical analyses to validate and evaluate our proposed ISACP scheme.**

***Index Terms*—Next generation wireless networks, integrated sensing and communication (ISAC), energy-harvesting, ISACP, massive MIMO, hypothesis testing, Cramér-Rao bound (CRB).**

## I. Introduction

THE next-generation wireless network is envisioned to support emerging applications with stringent requirements on quality-of-service (QoS), such as high data rate, low error probability, and high accuracy localization capability. To satisfy these stringent QoS requirements, the technique of *integrated sensing and communication (ISAC)* has been proposed to integrate the radar sensing and wireless communication functions using the shared spectrum, hardware platform, and signal processing frameworks. The radar sensing in ISAC is able to not only estimate positions of the targeted mobile users (MUs), but also can obtain the wireless channel state and fading by employing the estimated positions. *Simultaneous wireless information and power transfer (SWIPT)* has also been recognized as another key technique for the future energy-constrained or battery-limited wireless networks to convey both information and power using the same radio frequency signal. By employing the SWIPT, an energy-harvesting (EH) mobile device can adaptively harvest the power from its received signal and decode the information using the rest energy.

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Recent works have studied various ISAC and SWIPT schemes. The authors of [1] proposed the multi-input multi-output (MIMO) beamforming designs towards joint radar sensing and multi-user communications using ISAC and developed the performance metric of the target estimation. A point-to-point ISAC model under vector Gaussian channels was investigated by [2], based on which the authors proposed the Cramér-Rao bound (CRB)-rate region as a basic tool for depicting the fundamental sensing and communications tradeoff. The work of [3] studied an optimal power splitting-based SWIPT scheme for two communication systems wherein all receiving nodes are subject to a decoding cost. Considering the finite codelength coding, the authors of [4] analyzed the tradeoff between the rate and energy in SWIPT schemes and further characterized the fundamental performance of the SWIPT system by proposing a new tradeoff between the decoding error probability and the harvested energy.

However, how to jointly integrate the sensing, communication, and powering for the next-generation traffic to guarantee the stringent QoS provisioning has not been thoroughly studied. To address this issue, in this paper we propose an integrated sensing, communications, and powering (ISACP) scheme to support the QoS provisioning by employing massive multiple-input and multiple-output (massive MIMO) communications. Specifically, we define two power splitting ratios: the *communication-sensing power splitting ratio* determined by the massive MIMO base station (BS) when BS transmits the ISAC signal and the *decoding-EH power splitting ratio* determined by MUs when MUs receive the signal. First, we establish the system model to transmit and receive ISACP signals using these two power splitting ratios. Second, we develop a hypothesis testing based scheme to detect the MU and estimate the MU's angle-of-arrival through the sensing signal. Third, we employ the CRB to measure the performance of the radar sensing, derive the channel capacity to measure

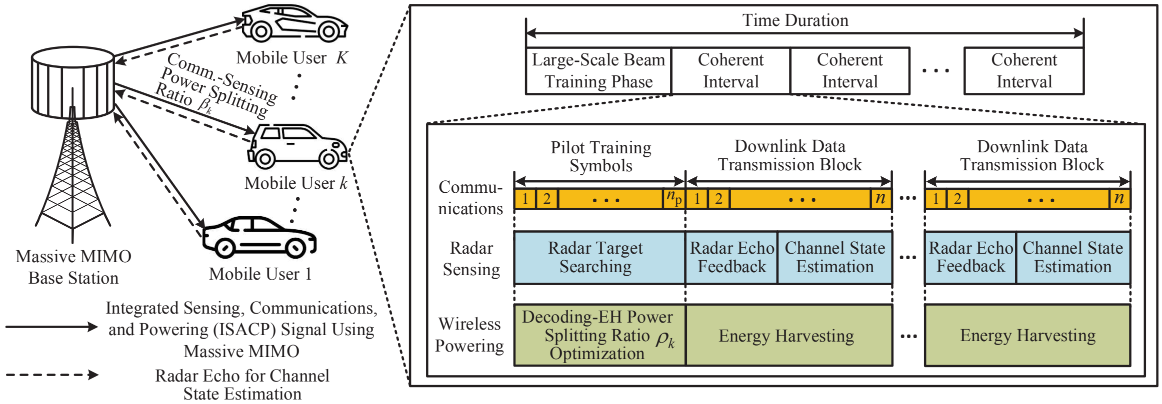


Fig. 1. The system architecture models of our proposed ISACP using massive MIMO, ISAC, and SWIPT techniques (with the finite blocklength equal to $n$ and the uplink pilot signal sequence length equal to $n_{\mathrm{p}}$) to perform: (1) the communications, to transmit the information to MUs with assigning $\beta_k, \forall k$, of the transmit power to the communication signal; (2) the radar sensing, to sense locations of MUs with assigning $(1-\beta_k), \forall k$, of the transmit power to the sensing signal; and (3) the wireless powering, to deliver the power to MUs with assigning $\rho_k$ of total received power to decode the communication signal and assigning $(1-\rho_k)$ of total received power to harvest the energy.

the performance of communications, and formulate an energy-efficiency maximization problem over all MUs while satisfying requirements of both sensing and communication QoS performances to support the next-generation traffic.

The rest of this paper is organized as follows. Section II establishes the system models for our proposed ISACP-based architectures. Section III proposes the schemes to detect MUs and estimate detected MUs' positions. Section IV employs the CRB to measure the estimation performance for targeted MUs' position and derives the channel capacity as the communication performance. Section V formulates an energy-efficiency maximization problem over all MUs. Section VI validates and evaluates our developed ISACP schemes. This paper concludes with Section VII.

## II. System Models for Our Proposed ISACP-Based Architectures Using Massive MIMO

As shown in Fig. 1, we consider a cellular network consisting of a massive MIMO BS and totally $K$ moving targeted MUs, where the massive MIMO BS sends the radar sensing and the downlink communication signals simultaneously to these $K$ targeted MUs. Assume that there are $M_T$ antennas on the BS and there are $M_R$ antennas on each targeted MU, where $M_T \gg M_R$. When the massive MIMO BS transmits the ISAC signal to MUs, it splits the total transmit power using the communication-sensing power splitting ratio $\beta_k, \forall k$, to assign $\beta_k$ and $(1-\beta_k)$ of the total power for the $k$th MU to the communication and sensing signal, respectively, where $0<\beta_k<1$. The $k$th MU, $\forall k$, splits the received radio frequency (RF) signals from the massive MIMO BS into two parts with decoding-EH power splitting ratios $\rho_k$ and $(1-\rho_k)$ for decoding the information and energy harvesting, respectively, where $0<\rho_k<1$.

In our proposed sensing scheme through the radar echo, each MU is considered as a scatterer to reflect the radar signal, and thus, the angle-of-arrival (AoA) and angle-of-departure (AoD) for each targeted MU are the same. The steering/response signal vector, denoted by $\mathbf{a}(M,\phi)$ for $M$ antennas and AoA/AoD equal to $\phi$, is defined as follows:

$$\mathbf{a}(M,\phi) \triangleq \left[1, e^{j\pi\sin(\phi)}, \dots, e^{j\pi(M-1)\sin(\phi)}\right]^{\mathsf{T}}, \quad (1)$$

where $(\cdot)^{\mathsf{T}}$ is the transpose operation. For the $k$th MU's radar-echo and radar-signal, let $\phi_k$ be the AoA and AoD of the $k$th MU (where AoA is equal to AoD for radar sensing). Define $\mathbf{S}^{\text{sen}} \in \mathbb{C}^{M_T\times M_T}$ as the target response matrix from the BS to the targeted MUs and reflected back to BS, which is given by

$$\mathbf{S}^{\text{sen}} = \sum_{k=1}^{K} \mu_k \mathbf{a}(M_T,\phi_k)\mathbf{a}(M_T,\phi_k)^{\mathsf{T}} \quad (2)$$

where $\mu_k$ is the amplitude of a complex value, characterizing both the signal attenuation and initial phase difference for the radar signal between the massive MIMO BS and the $k$th MU.

For the massive MIMO downlink communications, we denote by $\mathbf{S}_k^{\text{com}} \in \mathbb{C}^{M_R\times M_T}$ the communication channel state matrix, representing the channel state between all antennas on the $k$th targeted MU and all antennas on the massive MIMO BS. Let $\ell$ be the index of the multipath set $\{1,2,\dots,L\}$ between the $k$th targeted MU and the BS. Also, let $\widetilde{\mu}_{k,\ell}$ be the complex scattering coefficient of the $\ell$th multipath. Further, let $\xi_{k,\ell}$ and $\psi_{k,\ell}, \forall \ell \in \{1,\dots,L\}$, denote the AoA and AoD, respectively, of the $\ell$th downlink communication multipath for the $k$th targeted MU. Then, let $\widetilde{\mu}_{k,0}$, $\xi_{k,0}$, and $\psi_{k,0}$ be the channel coefficient, AoA, and AoD, respectively, of the line-of-sight path between the BS and MU $k$. The communication channel state matrix $\mathbf{S}_k^{\text{com}}$ is given by

$$\mathbf{S}_k^{\text{com}} \triangleq \widetilde{\mu}_{k,0}\mathbf{a}(M_R,\xi_{k,0})\mathbf{a}(M_T,\psi_{k,0})^{\mathsf{T}} + \sum\nolimits_{\ell=1}^{L} \widetilde{\mu}_{k,\ell}\mathbf{a}(M_R,\xi_{k,\ell})\mathbf{a}(M_T,\psi_{k,\ell})^{\mathsf{T}}. \quad (3)$$

Let $B_k$ be the total power allocation for the $k$th MU's sensing and communication signal and define $\mathbf{B} \triangleq [B_1, B_2, \cdots, B_K]^{\mathsf{T}}$ as the total power allocation vector for all $K$ MUs. For each $B_k, \forall k$, we set the the communication-sensing power splitting ratio as $\beta_k$ such that the power for communication signal of the $k$th MU is $\beta_k B_k$ and the power for the sensing signal of the $k$th MU is $(1-\beta_k)B_k$. Let $\mathbf{x}_i(\mathbf{B}) \in \mathbb{C}^{M_T\times 1}$ be the transmitted signal under the total power allocation vector $\mathbf{B}$ for the $i$th symbol, $\forall i \in \{1,\cdots,n\}$, from the massive MIMO BS to all $K$ MUs, which is given by [5, Eq. (1)] [6, Eq. (1)]

$$\mathbf{x}_i(\mathbf{B}) = \mathbf{W}^{\text{com}}(\mathbf{B}^{\text{com}})\mathbf{q}_i^{\text{com}} + \mathbf{W}^{\text{sen}}(\mathbf{B}^{\text{sen}})\mathbf{q}_i^{\text{sen}} \tag{4}$$

where $\mathbf{B}^{\text{com}} \triangleq [\beta_1 B_1,\cdots,\beta_K B_K]^\intercal$, $\mathbf{B}^{\text{sen}} \triangleq [(1-\beta_1)B_1,\cdots,(1-\beta_K)B_K]^\intercal$ with $\mathbf{B} = \mathbf{B}^{\text{sen}} + \mathbf{B}^{\text{com}}$, $\mathbf{W}^{\text{com}}(\mathbf{B}^{\text{com}}) \in \mathbb{C}^{M_T\times KM_R}$ and $\mathbf{W}^{\text{sen}}(\mathbf{B}^{\text{sen}}) \in \mathbb{C}^{M_T\times KM_R}$ are the communication and sensing precoders for all $K$ targeted MUs, respectively, under the total power allocation vector $\mathbf{B}$; and $\mathbf{q}_i^{\text{com}} \in \mathbb{C}^{KM_R\times 1}$ and $\mathbf{q}_i^{\text{sen}} \in \mathbb{C}^{KM_R\times 1}$ are the $i$th communication symbol and the $i$th probing sensing symbol, respectively.

Since all MUs are EH devices, the $k$th MU, $\forall k$, uses $\rho_k$ portion of the energy to receive information and harvests the rest $(1-\rho_k)$ portion of the energy. Denote by $\widetilde{\mathbf{B}} \triangleq [\rho_1 B_1, \rho_2 B_2,\cdots,\rho_K B_K]^\intercal$ the vector for the signal power after MUs' energy harvesting. After MUs' energy harvesting, the reflected radar echo signal for the $i$th symbol under the signal power vector $\widetilde{\mathbf{B}}$, denoted by $\mathbf{y}_i^{\text{sen}}(\widetilde{\mathbf{B}}) \in \mathbb{C}^{M_T\times 1}$, received by the massive MIMO BS is given by

$$\mathbf{y}_i^{\text{sen}}(\widetilde{\mathbf{B}}) = \mathbf{S}^{\text{sen}}\mathbf{x}_i(\widetilde{\mathbf{B}}) + \mathbf{v}^{\text{sen}},\ \forall i \in \{1,2,\cdots n\} \tag{5}$$

where $\mathbf{S}^{\text{sen}}$ is given by Eq. (2), $\mathbf{x}_i(\widetilde{\mathbf{B}}) \in \mathbb{C}^{M_T\times 1}$ can be obtained by replacing $\mathbf{B}$ in $\mathbf{x}_i(\mathbf{B})$ of Eq. (4) by $\widetilde{\mathbf{B}}$, $\mathbf{v}^{\text{sen}} \in \mathbb{C}^{M_T\times 1}$ is additive white Gaussian noise (AWGN) following a complex Gaussian distribution $\mathcal{CN}(\mathbf{0},\sigma_w^2\mathbf{I}_{M_T})$ at all $M_T$ antennas deployed in the massive MIMO BS, where $\sigma_w^2$ is the variance of any element in $\mathbf{v}^{\text{sen}}$ and $\mathbf{I}_{M_T}$ is the identity matrix of size $M_T$, and $n$ is the length of a data block.

## III. Targeted MUs' Detections and Estimations

### A. Targeted MUs' Detections Using Hypothesis Testing

Define the covariance matrix, denoted by $\mathbf{R}_{\mathbf{x}}(\widetilde{\mathbf{B}}) \in \mathbb{C}^{M_T\times M_T}$, of $\mathbf{x}_i(\widetilde{\mathbf{B}})$ as follows:

$$\mathbf{R}_{\mathbf{x}}(\widetilde{\mathbf{B}}) \triangleq \frac{1}{n}\sum_{i=1}^{n}\mathbf{x}_i(\widetilde{\mathbf{B}})\left(\mathbf{x}_i(\widetilde{\mathbf{B}})\right)^H \tag{6}$$

where $(\cdot)^H$ denotes the conjugate transpose operation, and $\mathbf{R}_{\mathbf{x}}(\widetilde{\mathbf{B}})$ can be decomposed using singular value decomposition as $\mathbf{R}_{\mathbf{x}}(\widetilde{\mathbf{B}}) = \mathbf{U}\boldsymbol{\Lambda}\mathbf{U}^H$, where $\mathbf{U}$ and $\boldsymbol{\Lambda}$ are matrices of eigenvectors and eigenvalues of $\mathbf{R}_{\mathbf{x}}(\widetilde{\mathbf{B}})$, respectively. Then, using $\mathbf{U}$ and $\boldsymbol{\Lambda}$, the linear transformation of $\mathbf{x}_i(\widetilde{\mathbf{B}})$, denoted by $\widetilde{\mathbf{x}}_i(\widetilde{\mathbf{B}})$, can be defined as:

$$\widetilde{\mathbf{x}}_i(\widetilde{\mathbf{B}}) \triangleq \boldsymbol{\Lambda}^{\frac{1}{2}}\mathbf{U}^H\mathbf{x}_i(\widetilde{\mathbf{B}}). \tag{7}$$

Define the $l$th sufficient statistics, denoted by $\boldsymbol{\eta}_l(\widetilde{\mathbf{B}}) \in \mathbb{C}^{M_T\times 1}$ and the $l$th independent sufficient statistics, denoted by $\widetilde{\boldsymbol{\eta}}_l(\widetilde{\mathbf{B}}) \in \mathbb{C}^{M_T\times 1}$, $\forall l \in \{1,\cdots,M_T\}$, as follows:

$$\begin{cases} \boldsymbol{\eta}_l(\widetilde{\mathbf{B}}) \triangleq \dfrac{1}{\sqrt{n}}\sum_{i=1}^{n}\mathbf{y}_i^{\text{sen}}(\widetilde{\mathbf{B}})\left(x_{i,l}(\widetilde{\mathbf{B}})\right)^*, & (8)\\ \widetilde{\boldsymbol{\eta}}_l(\widetilde{\mathbf{B}}) \triangleq \dfrac{1}{\sqrt{n}}\sum_{i=1}^{n}\mathbf{y}_i^{\text{sen}}(\widetilde{\mathbf{B}})\left(\widetilde{x}_{i,l}(\widetilde{\mathbf{B}})\right)^*, & (9)\end{cases}$$

where $x_{i,l}(\widetilde{\mathbf{B}})$ and $\widetilde{x}_{i,l}(\widetilde{\mathbf{B}})$ are the $l$th element of $\mathbf{x}_i(\widetilde{\mathbf{B}})$ and $\widetilde{\mathbf{x}}_i(\widetilde{\mathbf{B}})$, respectively, representing the signal transmitted by the $l$th antenna of the massive MIMO BS and $(\cdot)^*$ denotes the conjugate operation.

Define independent sufficient statistics matrix as $\widetilde{\boldsymbol{\eta}}(\widetilde{\mathbf{B}}) \triangleq \left[\widetilde{\boldsymbol{\eta}}_1(\widetilde{\mathbf{B}}),\cdots,\widetilde{\boldsymbol{\eta}}_{M_T}(\widetilde{\mathbf{B}})\right]\mathbb{C}^{M_T\times 1}$, where each element $\widetilde{\boldsymbol{\eta}}_l(\widetilde{\mathbf{B}})$ is given by Eq. (9). According to [7], the independent sufficient statistics vector, denoted by $\widehat{\boldsymbol{\eta}} \in \mathbb{C}^{M_T^2\times 1}$, is given by

$$\widehat{\boldsymbol{\eta}} \triangleq \text{vec}\left(\widetilde{\boldsymbol{\eta}}(\widetilde{\mathbf{B}})\right) = \sum_{k=1}^{K}\mu_k\widetilde{\mathbf{A}}(\phi_k) + \widetilde{\mathbf{v}}^{\text{sen}} \tag{10}$$

where $\text{vec}(\mathbf{M})$ is the column vector obtained by stacking the columns of the matrix $\mathbf{M}$, $\widetilde{\mathbf{A}}(\phi_k) \in \mathbb{C}^{M_T^2\times 1}$ and $\widetilde{\mathbf{v}}^{\text{sen}} \in \mathbb{C}^{M_T^2\times 1}$ are given, respectively, by

$$\begin{cases} \widetilde{\mathbf{A}}(\phi_k) \triangleq \sqrt{n}\text{vec}\left(\mathbf{a}(M_T,\phi_k)\mathbf{a}(M_T,\phi_k)^\intercal\mathbf{U}\boldsymbol{\Lambda}^{\frac{1}{2}}\right) & (11)\\ \widetilde{\mathbf{v}}^{\text{sen}} \triangleq \dfrac{1}{\sqrt{n}}\text{vec}\left(\sum_{i=1}^{n}\mathbf{v}^{\text{sen}}\left(\widetilde{\mathbf{x}}_i(\widetilde{\mathbf{B}})\right)^H\right), & (12)\end{cases}$$

where $\widetilde{\mathbf{x}}_i(\widetilde{\mathbf{B}})$ is given by Eq. (7).

Using Eq. (10), we have two hypotheses for each targeted MU. We define $H_{0,k}$ as the hypothesis stating that no targeted MU $k$ is detected, and define $H_{1,k}$ as the hypothesis stating that there exists a detected MU $k$ , respectively, as follows:

$$\begin{cases} H_{0,k}: \widehat{\boldsymbol{\eta}} = \widetilde{\mathbf{w}}^{\text{sen}}, & (13)\\ H_{1,k}: \widehat{\boldsymbol{\eta}} = \mu_k\widetilde{\mathbf{A}}(\phi_k) + \widetilde{\mathbf{v}}^{\text{sen}}. & (14)\end{cases}$$

Denote by $\widehat{\eta}_u$ the $u$th element ($\forall u \in \{1,\cdots,M_T^2\}$) of $\widehat{\boldsymbol{\eta}}$. Then, we can derive the probability density function (PDF), denoted by $f_{0,k}(\widehat{\boldsymbol{\eta}})$, of $\widehat{\boldsymbol{\eta}}$ under the hypothesis $H_{0,k}$ as follows:

$$f_{0,k}(\widehat{\boldsymbol{\eta}}) = \prod_{u=1}^{M_T^2}\frac{1}{\sqrt{2\pi\sigma_w^2}}\exp\left\{-\frac{1}{2}\left(\frac{\widehat{\eta}_u}{\sigma_w}\right)^2\right\} \tag{15}$$

and denote by $f_{1,k}(\widehat{\boldsymbol{\eta}};\mu_k,\phi_k)$ the PDF of $\widehat{\boldsymbol{\eta}}$ for detecting $(\mu_k,\phi_k)$ from $\widehat{\boldsymbol{\eta}}$ under the hypothesis $H_{1,k}$. Observing Eq. (14), we obtain that $\widehat{\boldsymbol{\eta}}$ under the hypothesis $H_{1,k}$ follows $\mathcal{CN}\left(\mu_k\widetilde{\mathbf{A}}(\phi_k),\sigma_w^2\mathbf{I}_{M_T^2}\right)$, and thus, we can derive

$$\begin{aligned} f_{1,k}(\widehat{\boldsymbol{\eta}};\mu_k,\phi_k) &= \prod_{u=1}^{M_T^2}\frac{1}{\sqrt{2\pi\sigma_w^2}}\exp\left\{-\frac{1}{2}\left(\frac{\widehat{\eta}_u - \overline{\eta}_u(\mu_k,\phi_k)}{\sigma_w}\right)^2\right\}\\ &= g_1(\widehat{\boldsymbol{\eta}})g_2(\widehat{\boldsymbol{\eta}},\mu_k,\phi_k)g_3(\mu_k,\phi_k) \end{aligned} \tag{16}$$

where $\overline{\eta}_u(\mu_k,\phi_k)$ is the average of the $u$th element of $\mu_k\widetilde{\mathbf{A}}(\phi_k)$, $\forall u \in \{1,\cdots,M_T^2\}$, and

$$\begin{cases} g_1(\widehat{\boldsymbol{\eta}}) = \dfrac{1}{(2\pi\sigma_w^2)^{\frac{M_T^2}{2}}}\exp\left\{-\dfrac{1}{2\sigma_w^2}\sum_{u=1}^{M_T^2}\widehat{\eta}_u^2\right\}, & (17)\\ g_2(\widehat{\boldsymbol{\eta}},\mu_k,\phi_k) = \exp\left\{-\dfrac{1}{\sigma_w^2}\sum_{u=1}^{M_T^2}\widehat{\eta}_u\overline{\eta}_u(\mu_k,\phi_k)\right\}, & (18)\\ g_3(\mu_k,\phi_k) = \exp\left\{-\dfrac{1}{2\sigma_w^2}\sum_{u=1}^{M_T^2}[\overline{\eta}_u(\mu_k,\phi_k)]^2\right\}. & (19)\end{cases}$$

Thus, we can derive the log-likelihood testing ratio function, denoted by $Z_k(\widehat{\boldsymbol{\eta}})$, by using these two PDFs derived in Eq. (15) and Eq. (16) as follows:

$$Z_k(\widehat{\boldsymbol{\eta}}) \triangleq \log\left(\frac{f_{1,k}(\widehat{\boldsymbol{\eta}};\mu_k,\phi_k)}{f_{0,k}(\widehat{\boldsymbol{\eta}})}\right) = \frac{M_T^2}{2}\log(2\pi\sigma_w^2) - \frac{1}{\sigma_w^2}\mu_k\widehat{\boldsymbol{\eta}}^H\widetilde{\mathbf{A}}(\phi_k) - \frac{1}{2\sigma_w^2}\left\|\mu_k\widetilde{\mathbf{A}}(\phi_k)\right\|^2 \tag{20}$$

where $\|\cdot\|^2$ is the Euclidean norm. Then, we compare the obtained $Z_k(\widehat{\boldsymbol{\eta}})$ with predefined thresholds $\delta_{\text{low}}$ and $\delta_{\text{up}}$ ($\delta_{\text{low}} \le \delta_{\text{up}}$) and accept one hypothesis using the following rules:

$$\begin{cases}\text{Accept the hypothesis } H_0, \text{if } Z_k(\widehat{\boldsymbol{\eta}}) < \delta_{\text{low}};\\ \text{Accept the hypothesis } H_1, \text{if } Z_k(\widehat{\boldsymbol{\eta}}) > \delta_{\text{up}};\\ \text{Take another observation, if } \delta_{\text{low}} < Z_k(\widehat{\boldsymbol{\eta}}) < \delta_{\text{up}}.\end{cases} \tag{21}$$

### *B. Estimations for Targeted MUs' AoAs*

If accepting the hypothesis $H_1$, the massive MIMO BS detects the $k$th targeted MU and further estimates its AoA $\phi_k$. Otherwise, the massive MIMO BS makes the decision that there is no targeted MU by accepting the hypothesis $H_0$, since there is no radar echo detected in Eq. (13).

In the situation of accepting the hypothesis $H_1$ (i.e., detecting the $k$th targeted MU), we further estimate the AoA for the $k$th targeted MU. The sufficient statistics matrix, denoted by $\boldsymbol{\eta}(\widetilde{\mathbf{B}})$, is defined as $\boldsymbol{\eta}(\widetilde{\mathbf{B}}) \triangleq \left[\boldsymbol{\eta}_1(\widetilde{\mathbf{B}}), \boldsymbol{\eta}_2(\widetilde{\mathbf{B}}), \cdots, \boldsymbol{\eta}_{M_T}(\widetilde{\mathbf{B}})\right] \in \mathbb{C}^{M_T\times 1}$, where each element $\boldsymbol{\eta}_l(\widetilde{\mathbf{B}}), \forall l$, is given by Eq. (8). We can obtain the estimation $\widehat{\phi}_k$ for $k$th targeted MU AoA as follows [7, Eq. (32)]:

$$\widehat{\phi}_k(\widetilde{\mathbf{B}}) = \arg\max_{\phi_k} \frac{\left|\mathbf{a}^H(M_T,\phi_k)\boldsymbol{\eta}(\widetilde{\mathbf{B}})\mathbf{a}^*(M_T,\phi_k)\right|^2}{M_T\mathbf{a}^H(M_T,\phi_k)\left[\mathbf{R}_{\mathbf{x}}(\widetilde{\mathbf{B}})\right]^{\intercal}\mathbf{a}(M_T,\phi_k)} \tag{22}$$

where $\widehat{\phi}_k(\widetilde{\mathbf{B}})$ is the estimated $\phi_k$ under the power allocation $\widetilde{\mathbf{B}}$ after energy harvesting, and $\mathbf{R}_{\mathbf{x}}(\widetilde{\mathbf{B}})$ is given by Eq. (6). Applying the $k$th MU's estimated position $\widehat{\phi}_k(\widetilde{\mathbf{B}})$, we are able to obtain all multipaths for the $k$th MU's communication channel. Therefore, collecting all MU's multipaths, we can further obtain the estimated communication channel matrix for all MUs, denoted by $\widehat{\mathbf{S}}^{\text{com}}\left(\widehat{\boldsymbol{\phi}}(\widetilde{\mathbf{B}})\right) \in \mathbb{C}^{KM_R\times M_T}$, where $\widehat{\boldsymbol{\phi}}(\widetilde{\mathbf{B}}) \triangleq \left[\widehat{\phi}_1(\widetilde{\mathbf{B}}), \cdots, \widehat{\phi}_K(\widetilde{\mathbf{B}})\right]$ is the estimated AoA vectors for all MUs under the power allocation $\widetilde{\mathbf{B}}$ after energy harvesting.

## IV. The Cramér-Rao Bound for Radar Sensing and Channel Capacity for Communication

To measure the performance of our proposed ISACP scheme, we use Cramér-Rao bound to measure the performance of the radar sensing and use the channel capacity to measure the performance of communications.

### *A. The Cramér-Rao Bound for Radar Sensing*

We employ the *Cramér-Rao bound* [8] to measure the lower-bound for the variance of the estimated AoA/AoD, denoted by $\text{Var}\left[\widehat{\phi}_k(\widetilde{\mathbf{B}})\middle|\rho_k\beta_kB_k\right], \forall k$, under the decoding-EH power splitting ratio $\rho_k$, communication-sensing power splitting ratio $\beta_k$, and the total power allocation $B_k$, and define the *Cramér-Rao bound*, denoted by $CRB\left(\widehat{\phi}_k(\widetilde{\mathbf{B}}), \rho_k\beta_kB_k\right)$, as follows:

$$CRB\left(\widehat{\phi}_k(\widetilde{\mathbf{B}}), \rho_k\beta_kB_k\right) \triangleq \inf\left\{\text{Var}\left[\widehat{\phi}_k(\widetilde{\mathbf{B}})\middle|\rho_k\beta_kB_k\right]\right\} \overset{(a)}{=} \frac{\sigma_w^2}{2|\mu_k|^2n}\left\{\frac{\text{tr}\left(\mathbf{A}^H\mathbf{A}\mathbf{R}_{\mathbf{X}}\right)}{\text{tr}\left(\dot{\mathbf{A}}^H\dot{\mathbf{A}}\mathbf{R}_{\mathbf{X}}\right)\text{tr}\left(\dot{\mathbf{A}}^H\dot{\mathbf{A}}\mathbf{R}_{\mathbf{X}}\right) - \left|\text{tr}\left(\dot{\mathbf{A}}^H\mathbf{A}\mathbf{R}_{\mathbf{X}}\right)\right|^2}\right\} \tag{23}$$

where (a) is due to [9, Eq. (4)], the input signal matrix $\mathbf{X} \triangleq [\mathbf{x}_1(\widetilde{\mathbf{B}}), \cdots, \mathbf{x}_n(\widetilde{\mathbf{B}})] \in \mathbb{C}^{M_T\times n}$, where $n$ is the number of symbols in a data block, $\mathbf{R}_{\mathbf{X}} = (1/n)\mathbf{X}\mathbf{X}^H \in \mathbb{C}^{M_T\times M_T}$, $\sigma_w^2$ is the variance of AWGN, $\mathbf{A} \triangleq \mathbf{a}(M_T,\phi_k)\mathbf{a}(M_T,\phi_k)^{\intercal}$, $\dot{\mathbf{A}} \triangleq \partial\mathbf{A}/\partial\phi_k$, and $\text{tr}(\cdot)$ denotes the trace.

### *B. Communication's Signal-to-Noise Ratio Under ISACP Schemes*

Let $\mathbf{q}_{k,i}^{\text{com}} \in \mathbb{C}^{M_R\times 1}$ be the $i$th communication symbol sending to the $k$th targeted MU and let $\mathbf{q}_i^{\text{com}} = [\mathbf{q}_{1,i}^{\text{com}}, \ldots, \mathbf{q}_{K,i}^{\text{com}}]^{\intercal} \in \mathbb{C}^{KM_R\times 1}$ be the $i$th communication symbols for all $K$ MUs, defined following Eq. (4). In our proposed ISACP scheme, define the power allocations for communication signal, denoted by $\widetilde{\mathbf{B}}^{\text{com}}$, and sensing signal, denoted by $\widetilde{\mathbf{B}}^{\text{sen}}$, respectively, after the energy harvesting as follows:

$$\begin{cases}\widetilde{\mathbf{B}}^{\text{com}} \triangleq [\rho_1\beta_1B_1, \cdots, \rho_K\beta_KB_K]^{\intercal},\\ \widetilde{\mathbf{B}}^{\text{sen}} \triangleq [\rho_1(1-\beta_1)B_1, \cdots, \rho_K(1-\beta_K)B_K]^{\intercal}.\end{cases} \tag{24}$$

Denote by $\mathbf{W}_k^{\text{com}} \in \mathbb{C}^{M_T\times M_R}$ and $\mathbf{W}_k^{\text{sen}} \in \mathbb{C}^{M_T\times M_R}$ the communication and sensing signals beamforming matrixes (i.e., precoders) for the $k$th targeted MU, respectively, which can be expressed by

$$\begin{cases}\mathbf{W}^{\text{com}}(\widetilde{\mathbf{B}}^{\text{com}}) = \left[\sqrt{\frac{\rho_1\beta_1B_1}{M_T}}\mathbf{W}_1^{\text{com}}, \cdots, \sqrt{\frac{\rho_K\beta_KB_K}{M_T}}\mathbf{W}_K^{\text{com}}\right],\\ \mathbf{W}^{\text{sen}}(\widetilde{\mathbf{B}}^{\text{sen}}) = \left[\sqrt{\frac{\rho_1(1-\beta_1)B_1}{M_T}}\mathbf{W}_1^{\text{sen}}, \cdots, \sqrt{\frac{\rho_K(1-\beta_K)B_K}{M_T}}\mathbf{W}_K^{\text{sen}}\right].\end{cases} \tag{25}$$

The received ISACP signal for the $i$th symbol ($\forall i \in \{1, 2, \cdots, n\}$) through communication channels at all antennas on $K$ MUs, denoted by $\mathbf{y}_i^{\text{com}}\left(\widehat{\boldsymbol{\phi}}(\widetilde{\mathbf{B}})\right) \in \mathbb{C}^{KM_R\times 1}$, is given by

$$\begin{aligned}\mathbf{y}_i^{\text{com}}\left(\widehat{\boldsymbol{\phi}}(\widetilde{\mathbf{B}})\right) &= \mathbf{S}^{\text{com}}\mathbf{x}_i(\widetilde{\mathbf{B}}) + \mathbf{v}^{\text{com}}\\ &= \widehat{\mathbf{S}}^{\text{com}}\left(\widehat{\boldsymbol{\phi}}(\widetilde{\mathbf{B}})\right)\mathbf{W}^{\text{com}}(\widetilde{\mathbf{B}}^{\text{com}})\mathbf{q}_i^{\text{com}} + \widehat{\mathbf{S}}^{\text{com}}\left(\widehat{\boldsymbol{\phi}}(\widetilde{\mathbf{B}})\right)\mathbf{W}^{\text{sen}}(\widetilde{\mathbf{B}}^{\text{sen}})\mathbf{q}_i^{\text{sen}}\\ &\quad + \mathbf{v}^{\text{com}} - \widetilde{\mathbf{S}}^{\text{com}}\left(\widehat{\boldsymbol{\phi}}(\widetilde{\mathbf{B}})\right)\mathbf{W}^{\text{com}}(\widetilde{\mathbf{B}}^{\text{com}})\mathbf{q}_i^{\text{com}}\\ &\quad - \widetilde{\mathbf{S}}^{\text{com}}\left(\widehat{\boldsymbol{\phi}}(\widetilde{\mathbf{B}})\right)\mathbf{W}^{\text{sen}}(\widetilde{\mathbf{B}}^{\text{sen}})\mathbf{q}_i^{\text{sen}}\end{aligned} \tag{26}$$

where $\mathbf{v}^{\text{com}} \in \mathbb{C}^{KM_R\times 1}$ is the AWGN at all antennas of all targets, and $\widetilde{\mathbf{S}}^{\text{com}}\left(\widehat{\boldsymbol{\phi}}(\widetilde{\mathbf{B}})\right)$ is the estimation error use as a function of $\widehat{\boldsymbol{\phi}}(\widetilde{\mathbf{B}})$. Let $y_{m,i}^{\text{com}}\Big(\widehat{\boldsymbol{\phi}}(\widetilde{\mathbf{B}})\Big)$ be the $m$th row of the vector $\mathbf{y}_i^{\text{com}}\left(\widehat{\boldsymbol{\phi}}(\widetilde{\mathbf{B}})\right)$, representing the received ISACP signal at the $m$th antenna of all targeted MUs ($\forall m \in \{1,\ldots,KM_R\}$ and assuming that $m$ is the index for the antenna belonging to the $k$th targeted MU), and $y_{m,i}^{\text{com}}\left(\widehat{\boldsymbol{\phi}}(\widetilde{\mathbf{B}})\right)$ is given by

$$
\begin{aligned}
&y_{m,i}^{\text{com}}\Big(\widehat{\boldsymbol{\phi}}(\widetilde{\mathbf{B}})\Big)\\
&=\sqrt{\frac{\rho_k\beta_k B_k}{M_T}}\widehat{\mathbf{s}}_m^{\text{com}}\left(\widehat{\boldsymbol{\phi}}(\widetilde{\mathbf{B}})\right)\mathbf{w}_m^{\text{com}}q_{m,i}^{\text{com}}+\Omega_{m,i}\left(\widehat{\boldsymbol{\phi}}(\widetilde{\mathbf{B}})\right)
\end{aligned} \tag{27}
$$

where $\widehat{\mathbf{s}}_m^{\text{com}}\Big(\widehat{\boldsymbol{\phi}}(\widetilde{\mathbf{B}})\Big) \in \mathbb{C}^{1\times M_T}$ is the $m$th row of the matrix $\widehat{\mathbf{S}}^{\text{com}}\Big(\widehat{\boldsymbol{\phi}}(\widetilde{\mathbf{B}})\Big)$, $\mathbf{w}_m^{\text{com}} \in \mathbb{C}^{M_T\times 1}$ is the $m$th column of the matrix $\mathbf{W}^{\text{com}}(\widetilde{\mathbf{B}}^{\text{com}})$, $q_{m,i}^{\text{com}}$ is the $m$th element of $\mathbf{q}_i^{\text{com}}$, and $\Omega_{m,i}\left(\widehat{\boldsymbol{\phi}}(\widetilde{\mathbf{B}})\right)$ is the *effective additive noise* on the $m$th antenna of all MUs, including the AWGN noise and negligible inter-user interference, given by:

$$
\begin{aligned}
&\Omega_{m,i}\Big(\widehat{\boldsymbol{\phi}}(\widetilde{\mathbf{B}})\Big) \triangleq \sum_{u=1,u\neq m}^{kM_R}\left(\sqrt{\frac{\rho_u\beta_u B_u}{M_T}}\widehat{\mathbf{s}}_m^{\text{com}}\left(\widehat{\boldsymbol{\phi}}(\widetilde{\mathbf{B}})\right)\mathbf{w}_u^{\text{com}}q_{u,i}^{\text{com}}\right)\\
&+\widehat{\mathbf{s}}_m^{\text{com}}\Big(\widehat{\boldsymbol{\phi}}(\widetilde{\mathbf{B}})\Big)\mathbf{W}^{\text{sen}}(\widetilde{\mathbf{B}}^{\text{sen}})\mathbf{q}_i^{\text{sen}}+v_m^{\text{com}}\\
&-\widetilde{\mathbf{s}}_m^{\text{com}}\Big(\widehat{\boldsymbol{\phi}}(\widetilde{\mathbf{B}})\Big)\mathbf{W}^{\text{com}}(\widetilde{\mathbf{B}}^{\text{com}})\mathbf{q}_i^{\text{com}}-\widetilde{\mathbf{s}}_m^{\text{com}}\Big(\widehat{\boldsymbol{\phi}}(\widetilde{\mathbf{B}})\Big)\mathbf{W}^{\text{sen}}(\widetilde{\mathbf{B}}^{\text{sen}})\mathbf{q}_i^{\text{sen}}
\end{aligned} \tag{28}
$$

where $v_m^{\text{com}}$ is the $m$th row of the vector $\mathbf{v}^{\text{com}}$ and $B_u$ is the total transmit power allocation for an MU to which $u$ belongs. Using Eq. (27), we can derive the signal-to-noise ratio (SNR), denoted by $\varphi_m(\rho_k\beta_k B_k)$, on the $m$th antenna of MUs as follows:

$$
\varphi_m(\rho_k\beta_k B_k)=\frac{\rho_k\beta_k B_k \text{Var}\left[\widehat{\mathbf{s}}_m^{\text{com}}\Big(\widehat{\boldsymbol{\phi}}(\widetilde{\mathbf{B}})\Big)\mathbf{w}_m^{\text{com}}q_{m,i}^{\text{com}}\right]}{M_T\text{Var}\left[\Omega_{m,i}\Big(\widehat{\boldsymbol{\phi}}(\widetilde{\mathbf{B}})\Big)\right]} \tag{29}
$$

where $\text{Var}[\cdot]$ is the variance over all $n$ channel uses and $\Omega_{m,i}\Big(\widehat{\boldsymbol{\phi}}(\widetilde{\mathbf{B}})\Big)$ is given by Eq. (28). Using $\varphi_m(\rho_k\beta_k B_k)$ obtained in Eq. (29), we can derive the channel capacity, denoted by $C_k$, of the $k$th MU as follows:

$$
C_k=\sum_{m=(k-1)M_R+1}^{kM_R}\log_2(1+\varphi_m(\rho_k\beta_k B_k)), \tag{30}
$$

assuming that the $m$th antenna belongs to the $k$th MU.

## V. Maximizing Energy-Efficiency for ISACP

Define the decoding-EH power splitting ratio vector, denoted by $\boldsymbol{\rho}$, and the communication-sensing power splitting ratio vector, denoted by $\boldsymbol{\beta}$, for all $K$ MUs as follows:

$$
\begin{cases}\boldsymbol{\rho}\triangleq[\rho_1,\rho_2,\cdots,\rho_K]^{\intercal},\\ \boldsymbol{\beta}\triangleq[\beta_1,\beta_2,\cdots,\beta_K]^{\intercal}.\end{cases} \tag{31}
$$

Denote by $B(\boldsymbol{\rho},\boldsymbol{\beta})$ the total power consumption (Joule/sec) for the ISACP-based massive MIMO communications system under the decoding-EH power splitting ratio vector $\boldsymbol{\rho}$ and communication-sensing power splitting ratio vector $\boldsymbol{\beta}$, which is given by:

$$
\begin{aligned}
&B(\boldsymbol{\rho},\boldsymbol{\beta})=B_{\text{T}}+KB_{\text{R}}+\sum_{k=1}^{K}\rho_k B_k\\
&-\sum_{k=1}^{K}(1-\rho_k)B_k-\sum_{k=1}^{K}\Gamma_k(\rho_k,\beta_k)-\sum_{k=1}^{K}\sum_{\substack{m=\\(k-1)M_R+1}}^{kM_R}\Omega_{m,i}\Big(\widehat{\phi}_k(\widetilde{\mathbf{B}})\Big)
\end{aligned} \tag{32}
$$

where $B_{\text{T}}$ is a constant signal processing circuit power consumption in the massive MIMO BS, $B_{\text{R}}$ is a constant circuit power consumption of each MU, $\Gamma_k(\rho_k,\beta_k)$ is the energy harvested from the information signal at the $k$th MU given by:

$$
\Gamma_k(\rho_k,\beta_k)=\sum_{\substack{m=\\(k-1)M_R+1}}^{kM_R}\frac{\rho_k\beta_k B_k}{M_T}\text{Var}\Big[\widehat{\mathbf{s}}_m^{\text{com}}\Big(\widehat{\boldsymbol{\phi}}(\widetilde{\mathbf{B}})\Big)\mathbf{w}_m^{\text{com}}q_{m,i}^{\text{com}}\Big]. \tag{33}
$$

We define the overall *energy-efficiency* (bits/Joule/Hz), denoted by $E(\boldsymbol{\rho},\boldsymbol{\beta})$, for the ISACP-based massive MIMO communications system by a function of decoding-EH power splitting ratio vector $\boldsymbol{\rho}$ and communication-sensing power splitting ratio vector $\boldsymbol{\beta}$ defined in Eq. (31) as the total number of bits successfully conveyed to all $K$ MUs per Joule consumed energy, which is given by

$$
E(\boldsymbol{\rho},\boldsymbol{\beta})\triangleq\frac{\sum_{k=1}^{K}C_k}{B(\boldsymbol{\rho},\boldsymbol{\beta})} \tag{34}
$$

where $C_k$ is the $k$th MU's channel capacity given by Eq. (30), and $B(\boldsymbol{\rho},\boldsymbol{\beta})$ is the total power consumption given by Eq. (32). Then, we maximize the energy-efficiency $E(\boldsymbol{\rho},\boldsymbol{\beta})$ as follows:

$$
\begin{aligned}
&\max_{\boldsymbol{\rho},\boldsymbol{\beta}}\{E(\boldsymbol{\rho},\boldsymbol{\beta})\} \qquad (35)\\
&\text{s.t.: C1}: \ CRB\left(\widehat{\phi}_k(\widetilde{\mathbf{B}}),\rho_k\beta_k B_k\right)\leq CRB_{\max},\forall k\\
&\qquad \text{C2}: \ C_k\geq C_{\min},\forall k
\end{aligned}
$$

where $CRB\left(\widehat{\phi}_k(\widetilde{\mathbf{B}}),\rho_k\beta_k B_k\right)$ in C1 is defined in Eq. (23), $C_k$ in C2 is the channel capacity of the $k$th MU defined in Eq. (30), $CRB_{\max}$ is the maximum tolerable Cramér-Rao bound, and $C_{\min}$ is the minimum required channel capacity.

## VI. Performance Evaluations

Figure 2 shows the Cramér-Rao bound $CRB\left(\widehat{\phi}_k(\widetilde{\mathbf{B}}),\rho_k\beta_k B_k\right)$ under different values of the decoding-EH power splitting ratio $\rho_k$ for the $k$th MU. We set the total power allocation for the $k$th MU $B_k=3$W, the actual AoA/AoD for $k$th MU $\phi_k=30^{\circ}$, and the number of receiving antennas on each MU $M_R=4$. Figure 2 shows that the Cramér-Rao bound decreases as the decoding-EH power splitting ratio $\rho_k$ increases. This is because a larger $\rho_k$ yields a larger power allocation for the integrated sensing and communication signal, and thus, yields a smaller variance for the targeted MU position sensing result. We can also observe from Fig. 2 that Cramér-Rao bound also decreases as the number of antennas $M_T$ on the BS increases, showing that a

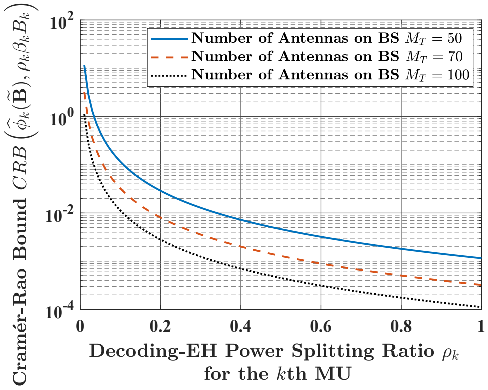


Fig. 2. Cramér-Rao bound $CRB\left(\widehat{\phi}_k(\widetilde{\mathbf{B}}), \rho_k\beta_k B_k\right)$ under different values of the decoding-EH power splitting ratio $\rho_k$.

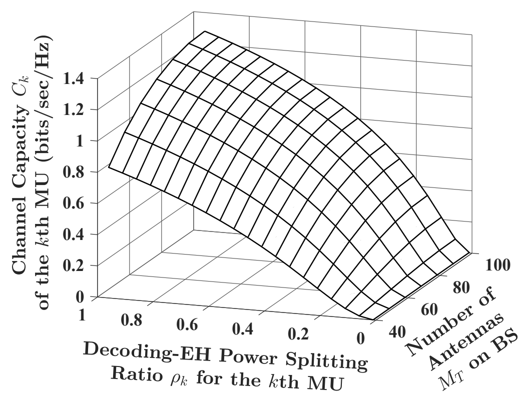


Fig. 3. Channel capacity $C_k$ for the $k$th MU under different values of the decoding-EH power splitting ratio $\rho_k$ and the number of antennas $M_T$ on the massive MIMO BS.

larger number of radar antennas can improve the radar sensing performance. Figure 2 also shows that when the decoding-EH power splitting ratio $\rho_k$ is 0.4, the Cramér-Rao bounds for all numbers of antennas are less than $10^{-2}$, showing that setting $\rho_k$ near $0.4$ is able to obtain an accurate sensing result.

Figure 3 shows the channel capacity $C_k$ for the $k$th MU under different values of the decoding-EH power splitting ratio $\rho_k$ and the number of antennas $M_T$ on the massive MIMO BS. We set the parameters in Fig. 3 the same as in Fig. 2. Figure 3 shows that the channel capacity $C_k$ increases as the decoding-EH power splitting ratio $\rho_k$ increases, since the SNR $\varphi_m(\rho_k\beta_k B_k)$ given by Eq. (29) increases as the power allocation for the communication signal increases. Figure 3 also shows that the channel capacity $C_k$ increases as the number of antennas $M_T$ on the massive MIMO BS increases for the same power allocation, implying that a larger $M_T$ can also improve the communication performance.

Figure 4 plots the $k$th MU's energy-efficiency $E(\rho_k, \beta_k)$ under different values of the decoding-EH power splitting ratio $\rho_k$ and communication-sensing power splitting ratio $\beta_k$ for the $k$th MU. Figure 4 reveals that there always exists an optimal pair $(\rho_k, \beta_k)$ for the $k$th MU to maximize its energy-efficiency, and thus, there exists an optimal vector pair $(\boldsymbol{\rho}, \boldsymbol{\beta})$ for all MUs, to maximize the overall energy-efficiency $E(\boldsymbol{\rho}, \boldsymbol{\beta})$ given by Eq. (35). We observe from Fig. 4 that the optimal decoding-EH power splitting ratio $\rho_k$ decreases as communication-sensing power splitting ratio $\beta_k$ increases, showing that these two

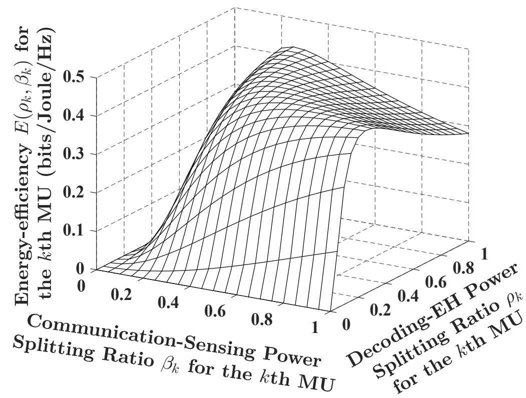


Fig. 4. Energy-efficiency $E(\rho_k, \beta_k)$ under different values of the decoding-EH power splitting ratio $\rho_k$ and communication-sensing power splitting ratio $\beta_k$ for the $k$th MU.

power splitting ratios can compensate for each other to achieve the same energy-efficiency $E(\rho_k, \beta_k)$.

## VII. Conclusions

To support the QoS provisioning for traffics over the next-generation wireless networks, we have proposed the ISACP schemes to integrate the ISAC with the SWIPT techniques to simultaneously sense the wireless channel, and transfer the information and power. We have applied the hypothesis testing to detect the targeted MUs and have derived their estimated AoA using the radar sensing signal. We have also obtained the Cramér-Rao bound and channel capacity to measure the radar sensing and communication performances, respectively. By optimizing the communication-sensing and the decoding-EH power splitting ratios, we have maximized the energy-efficiency over all MUs in our proposed ISACP schemes.

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