RIS-Assisted Device Activity Detection With Statistical Channel State Information

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Abstract—This paper studies reconfigurable intelligent surface (RIS)-assisted device activity detection for grant-free (GF) uplink transmission in wireless communication networks. In particular, we consider mobile devices located in an area where the direct link to an access point (AP) is blocked, thus, the devices try to connect to the AP via a reflected link provided by an RIS. Therefore, for the RIS, a phase-shift design is desired that covers the entire blocked area with a wide reflection beam because the exact locations and times of activity of the devices are unknown in GF transmission. In order to study the impact of the phase-shift design on the device activity detection at the AP, we derive a generalized likelihood ratio test (GLRT) based detector and present an analytical expression for the probability of detection, which is a function of the channel statistics and the phase-shift design. Assuming knowledge of statistical channel state information (CSI), we formulate an optimization problem for the phase-shift design for maximization of the guaranteed probability of detection for all locations within a given coverage area. To tackle the non-convexity of the problem, we propose two different approximations of the objective function and an algorithm based on the majorization-minimization (MM) principle. The first approximation leads to a design that aims to reduce the variations of the end-to-end channel while taking system parameters such as transmit power, noise power, and probability of false alarm into account. The second approximation can be adopted for versatile RIS deployments because it only depends on the line-of-sight (LoS) component of the end-to-end channel and is not affected by system parameters. For comparison, we also consider a phase-shift design maximizing the average channel gain and a baseline analytical phase-shift design for large blocked areas. Our performance evaluation shows that the proposed approximations result in phase-shift designs that guarantee a high probability of detection across the coverage area and outperform the baseline designs.

Index Terms—Device activity detection, reconfigurable intelligent surface, coverage extension, grant-free uplink, statistical channel state information, phase-shift design.

I. INTRODUCTION

It is unable to control the reflection properties of electromagnetic waves were proposed several years ago [2]. Recently, this technology has received significant attention in the wireless communications community, where metasurfaces are studied in the context of, e.g., holographic multiple-input multiple-output (MIMO) surfaces and reconfigurable intelligent surfaces (RISs) [3], [4]. In this paper, we focus on RISs which are low-cost passive devices that are able to reflect impinging electromagnetic waves in a desired direction by suitably adjusting their surface impedance. This ability of creating a smart radio environment helps in meeting the high performance requirements of future wireless networks [5]. An RIS is implemented as an array of small tunable elements (unit cells), each configured with an individual phase shift, and the phase-shift configuration of all unit cells is called the phase-shift design. Methods for efficient computation of the phase shifts were proposed in several works, including analytical designs [6], [7], optimized designs [8], [9], and algorithms exploiting instantaneous [10], [11] or statistical [12], [13] channel state information (CSI).

Recently, RIS-assisted communication networks were studied in the context of spectrum sensing and grant-free (GF) transmission, where protocol design and device activity detection are crucial building blocks for successful communication [14], [15], [16], [17], [18], [19]. For example, protocols for GF access were developed to reduce the number of signal collisions and improve system throughput, access probability, and access fairness [14], [15]. Moreover, the authors of [16], [17], [18], and [19] studied device activity detection and proposed frameworks that are independent of a specific phase-shift design. In particular, the central limit theorem was applied to obtain an approximate channel distribution that is independent of the phase shifts [16], [17]. Moreover, in [18], the RIS was configured to maximize the average channel gain, which decouples phase-shift design and detection performance.
analysis. Furthermore, a uniform phase distribution across the RIS was assumed in [19].

However, the frameworks proposed in [14], [15], [16], [17], [18], and [19] are not applicable to the location-dependent analysis of the detection performance because the impact of the angle-dependent reflection characteristics of the RIS are not considered. In fact, when the channels are sparse in the angular domain and the number of propagation paths is limited, as is expected, e.g., at millimeter-wave frequencies [20], the phase-shift design may have a significant impact on the device activity detection performance. In this case, it is important to employ a phase-shift design that takes the incident and reflected angles at the RIS into account [6]. Otherwise, device activity detection at the access point (AP) may fail because the devices' locations are not covered by the RIS reflection pattern [21]. Thus, a detailed analysis of the relation between phase-shift design and detection performance is required to ensure connectivity in RIS-assisted communication systems operating in the GF mode. To the best of the authors' knowledge, such analysis is not available in the existing RIS literature.

Motivated by the above discussion, in this paper, we study RIS phase-shift design for device activity detection for GF systems. In particular, we consider a communication network where the direct link from the AP to a pre-defined area is blocked. Thus, an RIS is deployed to connect the AP with mobile devices located in the blocked area through a reflected link. Intuitively, since the devices' exact locations and transmission times are unknown for GF access, the challenge is to develop a phase-shift design, only based on statistical CSI, which covers the entire area of interest with a wide reflection beam. To this end, we propose a generalized likelihood ratio test (GLRT) based detector and formulate an optimization problem that maximizes the probability of detection across all locations within the blocked area. Since the optimization problem is non-convex and involves the Marcum Q function, we reformulate the problem considering two approximations of the Marcum Q function and solve it applying the majorization-minimization (MM) principle, where each approximation results in a different phase-shift design. Finally, we adopt the proposed GLRT detector to evaluate the detection performance of these designs. For comparison, we consider an alternative design approach that maximizes the average channel gain and a baseline analytical design. The main contributions of this paper can be summarized as follows:

- We formulate the phase-shift design as an optimization problem for maximization of the minimum probability of detection across all locations within a given coverage area. In order to tackle the non-convexity of the problem, we propose two approximations for the objective function and reformulate them as differences-of-convex (DC) functions. This allows us to solve the problem by exploiting the MM principle and we obtain a high-quality suboptimal phase-shift design for each approximation.
- We evaluate the detection performance for the proposed design approach and show that our method outperforms existing schemes for RIS phase-shift design. In particular, the proposed design approach improves the probability of device activity detection compared to a design maximizing the average channel gain [22], [23], [24] and an analytical phase-shift design for large coverage areas [1], [7].

Different from its conference version [1], this paper takes both the LoS and NLoS paths of the device-RIS channels into account. As a result, the detection performance cannot be expressed as a monotonic function of the LoS channel gain as in [1], i.e., a different approach for phase-shift design is required. Similar to [1], the design proposed in this work is based on a non-convex optimization problem. However, instead of resolving the non-convexity of the problem using semidefinite relaxation and Gaussian randomization, we rewrite the non-convex terms in DC form and apply the MM principle. In addition, we investigate the impact of different transmit powers, scattering strengths, incident angles at the RIS, and area sizes. We also study the reflection patterns of the optimized phase-shift designs.

The remainder of this paper is organized as follows. Section II introduces the system and channel models. The GLRT for the considered device activity detection problem is derived in Section III. We formulate the optimization problem for the phase-shift design in Section IV, and present the MM based solution in Section V. The performance of the proposed phase-shift designs is evaluated in Section VI, and conclusions are drawn in Section VII.

Notations: \(\text{Tr}(\cdot), (\cdot)^T, (\cdot)^H, (\cdot)^{-1}\), and \(\mathbb{E}[\cdot]\) denote the trace, transpose, conjugate transpose, inverse, and expectation operations, respectively. \(\|\cdot\|\) refers to the Euclidean norm of a vector and \(|\cdot|\) represents the absolute value of a scalar. The nuclear norm and spectral norm of a matrix are denoted by \(\|\cdot\|_\text{F}\) and \(\|\cdot\|_2\), respectively. Given a function \(f(\mathbf{X})\) with matrix argument \(\mathbf{X}\), \(\nabla_{\mathbf{X}} f\) represents the gradient of \(f(\mathbf{X})\). The element in the \(m\)th row and \(n\)th column of a matrix and the \(m\)th and \(n\)th element of a vector are denoted by \([\cdot]_{m,n}\) and \([\cdot]_n\), respectively. The determinant of matrix \(\mathbf{X}\) is denoted by \(\det(\mathbf{X})\), the identity matrix is denoted by \(\mathbf{I}\), and a positive semidefinite matrix \(\mathbf{X}\) is denoted by \(\mathbf{X} \succeq 0\). \(\mathbb{R}\) and \(\mathbb{C}\) represent the sets of real and complex numbers, respectively. \(\mathbf{x} \sim \mathcal{CN}(\mathbf{a}, \mathbf{B})\) refers to a complex normally distributed random vector \(\mathbf{x}\) with mean vector \(\mathbf{a}\) and covariance matrix \(\mathbf{B}\). \(\chi^2_{a}(b)\) represents a non-central chi-squared distribution with \(a\) degrees of freedom and non-centrality parameter \(b\). Probability is denoted by \(\Pr[\cdot]\). The operator \(|x|\) represents the largest integer less than or equal to \(x\) and the remainder of the division.
a/b is denoted by \(a \pmod{b}\). The exponential function \(e^{(\cdot)}\) is also written as \(\exp(\cdot)\).

II. SYSTEM MODEL

In this section, we present the considered communication network, where the direct link from the AP to a specific area is blocked. As illustrated in Fig. 1, mobile devices located within the blocked area connect to the AP via the reflected link of the RIS. In the following, we introduce the coordinate system for the communication network and describe the coverage area, the RIS, and the AP in more detail. Additionally, we present the adopted channel model.

A. Coordinate System

We place the origin of the coordinate system at the center of the RIS and refer to a location in three-dimensional space as \(q\). Location \(q\) is specified by Cartesian coordinates \(\text{cart}(q) = (x_q, y_q, z_q)\) or spherical coordinates \(\text{sph}(q) = (d_q, \theta_q, \phi_q)\), where \(d_q, \theta_q, \phi_q\) denote the distance from the origin to \(q\), the elevation angle of \(q\), and the azimuth angle of \(q\), respectively. Further, we denote the direction from the origin to location \(q\) as \(\Psi(q) = (\theta_q, \phi_q)\).

B. Coverage Area and Transmitters

In this work, without loss of generality, we assume a rectangular coverage area in the \(y-z\) plane with center coordinates \((c_x, c_y, c_z)\), length \(D_z\) in \(z\)-direction, and width \(D_y\) in \(y\)-direction. For tractability, we take \(Q\) samples of the continuous coverage area based on a regular grid and obtain an approximated coverage area characterized by the discrete set of locations \(Q = \{q_{1,1}, q_{1,2}, \ldots, q_{Q}\}\). The number of samples can be chosen according to the desired approximation accuracy [1]. The location of a device is denoted as \(q_t\), where \(q_t \in Q\) holds for devices located within the coverage area. We consider single-antenna devices that try to connect to the AP by transmitting a preamble sequence, which is defined by symbol vector \(s \in \mathbb{C}^S\) of length \(S\). We assume normalized symbols, i.e., \(\|s\|_2^2 = 1, \forall s \in \{1, \ldots, S\}\).

C. Access Point

We consider an \(M\)-antenna AP deployed at a fixed and known location \(q_r\). Furthermore, we assume a LoS link\(^1\) between RIS and AP, and assume that the beamforming vector of the AP aligns with the incident angle of the RIS-AP LoS link. Since the locations of both AP and RIS are fixed, the incident angle and the beamforming vector do not change. Thus, the AP can be modeled as an equivalent single-antenna receiver with beamforming gain \(M\). For an active device at a given location \(q_t\), the received signal at the AP is given by

\[
x = h \sqrt{M P_k s + n},
\]

where \(h \in \mathbb{C}, P_k \in \mathbb{R}, \text{ and } n \in \mathbb{C}^S\) denote the end-to-end channel gain, the transmit power, and additive Gaussian noise, respectively. The noise is modeled as \(n \sim \mathcal{CN}(0, \sigma^2 I)\) with noise power \(\sigma^2\). Note that \(h\) depends on the phase-shift design and the channel model, which is presented in Section II-E.

D. Reconfigurable Intelligent Surface

It has been shown that the reflection gain of the RIS depends on the angles of arrival (AoAs) and angles of departure (AoDs) of the incident and reflected waves, respectively [6], [27], [28]. Therefore, in order to correctly model the reflection gain for the different device locations, we adopt the physics-based RIS model from [6]. In particular, we assume that the RIS is centered at the origin of the coordinate system and is modeled as a uniform planar array (UPA) with \(U_x U_y = U\) unit cells in the \(x-y\) plane. The location of unit cell \(u \in \{0, 1, \ldots, U - 1\}\) is given by the coordinate vector

\[
c_u = \left[\begin{array}{c} d_x u_x \\
d_y u_y \\
0 \end{array}\right]^T,
\]

where \(d_x\) and \(d_y\) denote the unit cell spacing along the \(x\) and \(y\) axis, respectively, and

\[
\begin{align*}
u_x &= u \text{ (mod } U_x) - U_x/2 + 1 \\
u_y &= u/ U_y - U_y/2 + 1.
\end{align*}
\]

Here, we assume that \(U_x\) and \(U_y\) are even numbers. The response function of the RIS is given by

\[
g(\Psi(q_r), \Psi(q_t)) = \frac{\sqrt{4\pi}}{\lambda} c(\Psi(q_r), \Psi(q_t)) w^H a(\Psi(q_r), \Psi(q_t)),
\]

where \(\lambda \in \mathbb{R}, c(\Psi(q_r), \Psi(q_t)) \in \mathbb{C}, w \in \mathbb{C}^U, \text{ and } a(\Psi(q_r), \Psi(q_t)) \in \mathbb{C}^U\) denote the wavelength, the unit cell factor, the phase-shift vector, and the array response, respectively. Defining

\[
k(\Psi(q)) = \frac{2\pi}{\lambda} \left[\sin(\theta_q) \cos(\phi_q) \sin(\theta_q) \sin(\phi_q) \cos(\theta_q)\right]^T
\]

\(^1\)In RIS-assisted networks, it is usually desired that the RIS is deployed with LoS to the AP in order to achieve the maximum possible received power [25], [26]. Thus, similar to [14], [22], [23], [25], and [26] we assume that, for the AP-RIS channel, the impact of fading is negligible and consider only the LoS path.

\(^2\)We first consider an active device at a given location \(q_t\), but we extend the analysis to all locations \(Q\) of the coverage area in Section IV. Moreover, multi-device activity detection is discussed in Remark 5.
and \(k(q_r, q_t) = k(\Psi(q_r)) + k(\Psi(q_t))\), the array response can be expressed as
\[
a(\Psi(q_r), \Psi(q_t)) = \left[ e^{j\Psi(q_r)}e_{c_1} \quad e^{j\Psi(q_t)}e_{c_1} \quad \ldots \quad e^{j\Psi(q_r)}e_{c_u-1} \right]^T.
\] (7)

The \(u\)th element of \(w\) is given by \(e^{j\omega_u}\), where \(\omega_u\) denotes the phase shift applied by the \(u\)th unit cell. Unit cell factor \(c(\Psi(q_r), \Psi(q_t))\) describes the amplitude of the reflection coefficient of each unit cell, which depends on the incident and reflected angles, the polarization of the incident wave, and the physical realization of the unit cells. For example, using the physics-based model of [6], the unit cell factor is given by
\[
c(\Psi(q_r), \Psi(q_t)) = \frac{j\sqrt{4\pi d_x d_y}}{\lambda} \cos(\theta_{q_t}) \sqrt{c_1^2 + c_2^2},
\] (8)
where
\[
\begin{align*}
\hat{c}_1 &= \cos(\varphi_{q_t}) \cos(\varphi_{r}) \sin(\varphi_{r}) - \sin(\varphi_{q_t}) \cos(\theta_{q_t}) \cos(\varphi_{r}) \\
\hat{c}_2 &= \sin(\varphi_{q_t}) \sin(\varphi_{r}) + \sin(\varphi_{q_t}) \cos(\theta_{q_t}) \sin(\varphi_{r}) \\
\hat{c}_3 &= \cos^2(\theta_{q_t}) + \cos(\varphi_{q_t}) \sin(\varphi_{r}) \cos(\theta_{q_t}) \sin(\varphi_{r}))^2
\end{align*}
\] (9)
and \(\varphi_{r}\) denotes the polarization of the incident wave originating from location \(q_r\).

### E. Channel Model

We assume that the direct link between the coverage area and the AP is blocked, cf. Fig. 1. Therefore, the devices have to connect with the AP via the reflected link, which comprises the device-RIS and the RIS-AP links. As stated in Section II-C, the RIS-AP link is dominated by the LoS path. For the device-RIS link, the scattered paths cannot be neglected because the devices are located close to the ground [29], [30]. Nevertheless, we assume a limited number of clusters of scatterers [6]. Furthermore, the clusters’ incident directions at the RIS are fixed and equal for all locations within the coverage area [29]. Therefore, the channel in (1) can be modeled as follows
\[
h = \hat{h}(q_r)g(\Psi(q_r), \Psi(q_t)) + \sum_{l=1}^{L} \eta_l(q_l)g(\Psi(q_l), \Psi(q_l)),
\] (12)
where \(L\), \(\Psi(q_l)\), and \(\eta_l(q_l) \sim \mathcal{CN}(0, \sigma_l^2(q_l))\) denote the number of clusters, the incident direction of the \(l\)th cluster on the RIS, and the small-scale fading with variance \(\sigma_l^2(q_l)\) caused by the \(l\)th cluster, respectively, and \(\hat{h}(q_r)\) denotes the LoS channel coefficient between the RIS and location \(q_r\). Note that the variances of the small-scale fading may change for different device locations, i.e., variance \(\sigma_l^2(q_l)\) depends on \(q_l\). In addition, similar to [8], [9], and [19], we assume narrow-band communication, i.e., the delays between different propagation paths are not resolvable. The channel gain \(\hat{h}(q_l)\) can be written as \(\hat{h}(q_l) = \hat{h}(q_l) e^{j\varphi(q_l)}\), where magnitude \(|\hat{h}(q_l)| = \lambda/(4\pi d_q)\) is given by the free-space path loss and depends on wavelength \(\lambda\) and distance \(d_q\) between location \(q\) and the RIS. The phase shift \(\varphi(q_l) = 2\pi d_q/\lambda\) depends on the wavelength and the distance as well.

**Remark 1:** In the following, we assume that \(\Psi(q_l)\) and \(\sigma_l^2(q_l), \forall l \in \{1, \ldots, L\}\), are known based on channel measurements for previous transmissions [31].

**Remark 2:** We note that, in practice, the accuracy of the (measured) distance \(d_q\) is limited and may not be in the order of the wavelength. As a result, we assume that the phase terms \(e^{j\varphi(q_r)}\) and \(e^{j\varphi(q_t)}\) are unknown [1]. In contrast, small deviations of \(d_q\) do not have a significant impact on the channel magnitude. Thus, we assume that \(|\hat{h}(q)|\) is known.

Substituting (5) in (12) allows us to rewrite the channel coefficient as follows
\[
h = w^H \left( h_{\text{LoS}} + h_{\text{NLoS}} \right),
\] (13)
where
\[
\begin{align*}
h_{\text{LoS}} &= \frac{\sqrt{4\pi}}{\lambda} \hat{h}(q_r) \hat{h}(q_t) c(\Psi(q_r), \Psi(q_t))a(\Psi(q_r), \Psi(q_t)) \\
h_{\text{NLoS}} &= \frac{\sqrt{4\pi}}{\lambda} \hat{h}(q_r) \sum_{l=1}^{L} \eta_l c(\Psi(q_l), \Psi(q_l))a(\Psi(q_l), \Psi(q_l)).
\end{align*}
\] (14a) (14b)

Based on (13), we note that phase-shift vector \(w\) has an impact on the end-to-end channel \(h\). Moreover, \(h_{\text{LoS}}\) in (14a) is deterministic and \(h_{\text{NLoS}}\) in (14b) is complex Gaussian distributed. Thus, end-to-end channel coefficient \(h\) in (13) is a linear combination of complex Gaussian random variables with its distribution given by \(h \sim \mathcal{CN}(w^H h_{\text{LoS}}, w^H C w)\), where
\[
C = 4\pi \frac{\lambda^2}{\lambda^2} \hat{h}(q_r) \sum_{l=1}^{L} \left( \sigma_l^2(q_l) c(\Psi(q_l), \Psi(q_l)) \right)^2 \times a(\Psi(q_r), \Psi(q_l))a^H(\Psi(q_r), \Psi(q_l)).
\] (15)

## III. Device Activity Detection

In this section, we consider the problem of device activity detection and derive analytical expressions for the detection performance. In general, for a given desired probability of false alarm, the maximum probability of detection of an active device is obtained with the likelihood ratio test (LRT) [32]. However, the LRT requires full knowledge of the distribution of the end-to-end channel. We observe from (14) and (15) that the variance of the channel is known, but the mean value depends on the unknown phase terms of the LoS paths, cf. Remark 2. Therefore, we use estimates of the unknown terms for the derivation of the detector, which results in a GLRT [32].

For derivation of the proposed detector, we exploit the following lemma.
Lemma 1: For $y, \tilde{y} \in \mathbb{C}^N$, $\zeta, \beta \in \mathbb{C}$, $r_1, r_2 \in \mathbb{R} \setminus \{0\}$, and $K = r_1\tilde{y}\tilde{y}^H + r_2I$, the following identity holds:

$$
\min_{\beta} (y - \tilde{y}\zeta\beta)^H K^{-1} (y - \tilde{y}\zeta\beta) = (y - \frac{1}{\tilde{y}H\tilde{y}}\tilde{y}\tilde{y}^H y)^H K^{-1} (y - \frac{1}{\tilde{y}H\tilde{y}}\tilde{y}\tilde{y}^H y).
$$

(16)

Proof: Given $U \in \mathbb{C}^{N \times p}$ and $K \in \mathbb{C}^{N \times N}$, let $y \sim \mathcal{CN}(U\mu, K)$ with the unknown vector $\mu \in \mathbb{C}^p$. Then, the maximum likelihood estimate (MLE) of $\mu$ is given by [33, Chapter 15]

$$
\hat{\mu} = \left(U^H K^{-1} U\right)^{-1} U^H K^{-1} y.
$$

(17)

The left-hand side of (16) is equivalent to finding the MLE of $\beta$ for $y \sim \mathcal{CN}(\tilde{y}\zeta\beta, K)$. Hence, with $U = \tilde{y}\zeta$ and $p = \beta$, we obtain the MLE

$$
\beta = \frac{1}{\tilde{y}H\tilde{y}}\tilde{y}^H K^{-1} y.
$$

(18)

The inverse of $K = r_1\tilde{y}\tilde{y}^H + r_2I$ is found with the Woodbury matrix identity (matrix inversion lemma) as

$$
K^{-1} = \frac{1}{r_2} \left(I - \frac{r_1\tilde{y}\tilde{y}^H}{r_2 + r_1\tilde{y}^H\tilde{y}}\right).
$$

(19)

Substituting (19) in (18) results in

$$
\hat{\beta} = \frac{1}{\tilde{y}H\tilde{y}} \tilde{y}^H y,
$$

(20)

which gives the value for $\beta$ that minimizes the left-hand side of (16). The right-hand side is obtained by substituting (20) for $\beta$ in (16).

A. Detection Problem

Device activity detection at the AP can be described as a binary hypothesis test problem [32]. More specifically, we define hypothesis $H_0$ for an inactive device and hypothesis $H_1$ for an active device. Hence, received signal $x$ can be written as

$$
H_0: x = n
$$

(21a)

$$
H_1: x = h\sqrt{P} s + n,
$$

(21b)

where (21a) contains noise only and (21b) follows from (1) with $P = MP_0s$ and $s = \sqrt{T}u$. Here, we normalize $s$ to obtain $\|s\|^2 = 1$, which simplifies the derivations in the following sections. Using the channel model in (13), we obtain

$$
H_0: x \sim \mathcal{CN}(0, C_0)
$$

(22a)

$$
H_1: x \sim \mathcal{CN}(\mu(\gamma), C_1),
$$

(22b)

where

$$
\gamma = e^{j(\varphi(q_t) + \varphi(q_s))}
$$

(23)

$$
\mu(\gamma) = w^H \sqrt{\frac{\lambda}{\alpha}} |h(q_t)||h(q_s)| \gamma
$$

$$
\times c(\Psi(q_t), \Psi(q_s))\Psi(q_t), \Psi(q_s)\sqrt{P} s
$$

(24)

$$
C_0 = \sigma^2 I
$$

(25)

$$
C_1 = w^H CW s s^H + \sigma^2 I.
$$

(26)

In (23) and (24), we introduce parameter $\gamma$ comprising the phase terms of the LoS links, which constitutes the unknown parameter for the GLRT.

B. Detection Metric

In general, the GLRT of a binary hypothesis test problem is based on a detection metric $T(x)$ that is derived from the likelihood ratio of both hypotheses. This metric is compared to a threshold $t$ and the detector assumes that $H_1$ is the true hypothesis when $T(x) > t$ holds for received signal $x$ [32].

For the problem at hand, the log-likelihood ratio for the hypotheses in (21) is given by [32]

$$
L_G(x, \gamma) = \log \left[ \frac{\det(C_0)}{\det(C_1)} \frac{\exp\left(-x^H C_0^{-1} x\right)}{\exp\left(-x^H C_1^{-1} x\right)} \right].
$$

(27)

The dependence on unknown parameter $\gamma$ is resolved by finding the best estimate $\hat{\gamma}$ for detection, i.e., finding $\hat{\gamma}$ that maximizes (27) [32]. Using Lemma 1, we obtain

$$
\max_{\gamma} L_G(x, \gamma) = \log \left[ \frac{\det(C_0)}{\det(C_1)} + x^H C_0^{-1} x \right. 
$$

$$
- (x - s s^H x)^H C_1^{-1} (x - s s^H x).
$$

(28a)

The first term in (28b) is independent of $x$ and can be neglected for detection. Thus, the detection metric of the GLRT is given by

$$
T(x) = x^H C_0^{-1} x - (x - s s^H x)^H C_1^{-1} (x - s s^H x)
$$

(29a)

$$
= x^H (C_0^{-1} - C_1^{-1}) x - x^H s s^H C_1^{-1} s s^H x
$$

$$
+ x^H C_1^{-1} s s^H x + x^H s s^H C_1^{-1} x.
$$

(29b)

Since $C_0^{-1} = \sigma^{-2} I$ and $C_1^{-1}$ is found with (19) and (26), (29) simplifies to

$$
T(x) = \frac{1}{\sigma^2 |s^H x|^2},
$$

(30)

which is a correlation detector for the known preamble sequence $s$.

C. Detection Performance

In order to determine the performance of detection metric (30), we examine the distribution of $T(x)$. Based on (21) and (22), (30) can be written as

$$
H_0: T(x) = \frac{1}{\sigma^2 |s^H n|^2} = \frac{1}{2} z_0
$$

(31a)

$$
H_1: T(x) = \frac{1}{\sigma^2} |s^H (h\sqrt{P} s + n)|^2 = \frac{w^H CW P + \sigma^2}{2\sigma^2} z_1.
$$

(31b)
where
\[
\begin{align*}
    z_0 &= \frac{2}{\sigma^2} \| s^H n \|^2 \sim \chi^2(0) \quad (32a) \\
    z_1 &= \frac{2}{w^H C w P + \sigma^2} \| s^H (h^T P s + n) \|^2 \\
    &\sim \chi^2 \left( 2P \left( \frac{w^H h_{\text{LoS}}^2}{w^H C w P + \sigma^2} \right) \right) . \quad (32b)
\end{align*}
\]

Thus, in general, the detection metric follows a scaled non-central chi-squared distribution, where both the scaling factor and the non-centrality parameter take different values under \( \mathcal{H}_0 \) and \( \mathcal{H}_1 \). The non-centrality parameter under \( \mathcal{H}_0 \) equals zero, i.e., the probability of false alarm is given by
\[
P_F = \Pr \left( \frac{1}{2} z_0 > t \right) = 1 - (1 - e^{-t}) . \quad (33)
\]

Thus, for a desired \( P_F \), the detection threshold is obtained as \( t = -\ln(P_F) \). The probability of detection is then given by
\[
P_D = \Pr \left( \frac{w^H C w P + \sigma^2}{2\sigma^2} z_1 > t \right) = \Pr \left( z_1 > \frac{-2\sigma^2 \ln(P_F)}{w^H C w P + \sigma^2} \right) . \quad (34a)
\]

Since \( z_1 \) is a non-central chi-squared random variable, (34) can be expressed as follows
\[
P_D = Q_1 \left( \frac{2P}{w^H C w P + \sigma^2} \sqrt{\frac{-2\sigma^2 \ln(P_F)}{w^H C w P + \sigma^2}} \right) , \quad (35)
\]

where \( Q_1(a, b) = \int_0^\infty t e^{-\frac{t^2 + a^2}{2}} I_0(at) dt \) denotes the first-order Marcum Q function for \( b > 0, a > 0 \), and \( I_0(\cdot) \) denotes the modified Bessel function of the first kind of order 0 [34].

**Remark 3:** The probability of detection in (35) depends on both the mean value and the variance of the end-to-end channel. If the variance is zero, i.e., the channel comprises the LoS path only, the second parameter of \( Q_1 \) in (35) becomes independent of \( w \). Then, \( P_D \) simplifies to the expression in [1, Eq. (19)], where the scattered paths of the device-RIS channels were not taken into account.

**Remark 4:** Instead of the proposed GLRT-based correlation detector, one could adopt an energy detector that evaluates \( \| x \|^2 \) for device activity detection. In this case, the detection metric follows a central chi-squared distribution with 2S degrees of freedom for \( \mathcal{H}_0 \) and a generalized chi-squared distribution for \( \mathcal{H}_1 \). The cumulative distribution functions of these distributions are not available in simple analytical form, which makes it challenging to formulate a suitable optimization problem for the RIS phase shifts for maximization of \( P_D \). Moreover, energy detection cannot be used for multi-device activity detection, but such feature may be beneficial for subsequent communication. Therefore, in this paper, we focus on the proposed GLRT-based correlation detector because it yields a tractable expression for \( P_D \) and supports multi-device activity detection with orthogonal preamble sequences, cf. Remark 5.

**IV. Phase-Shift Design**

In this section, we first formulate a non-convex optimization problem to obtain the optimal phase-shift design for device activity detection. In order to tackle the non-convexity, we reformulate the problem and propose two approximations of the objective function, each leading to a different suboptimal phase-shift design. The reformulated problem is solved with an algorithm exploiting the MM principle. Moreover, we investigate the maximization of the average channel gain as an alternative phase-shift design criterion.

**A. Optimal Phase-Shift Design**

Recall that the RIS is deployed to assist the detection of devices that try to connect to the AP, where the exact locations of the devices are not known. Therefore, we aim for a phase-shift design that maximizes the guaranteed detection performance, i.e., the minimum probability of detection for any device location within the coverage area. Since the probability of detection for an active device at a specific location is given by (35), the optimal phase-shift design is obtained based on

\[
\max_{w \in \mathbb{C}^l} \min_{q_i \in \mathbb{Q}} Q_1 \left( \frac{2P}{w^H C w P + \sigma^2} \sqrt{\frac{-2\sigma^2 \ln(P_F)}{w^H C w P + \sigma^2}} \right) . \quad (36a)
\]

\[
s.t. \quad \| w \|_u = 1, \quad \forall u \in \{0, \ldots, U - 1\} . \quad (36b)
\]

**Remark 5:** In addition to the considered single-device case, problem (36) can also be used to optimize the performance for multi-device activity detection. More specifically, consider \( Q_D \) devices located at some locations \( q_i \in \mathbb{Q} \) within the coverage area. Some of these devices may simultaneously become active and, due to sporadic access, one can assume that all active devices transmit orthogonal preamble sequences. Then, the correlation detector in (30) can independently be evaluated for each preamble. Moreover, we note that the distributions for \( \mathcal{H}_0 \) and \( \mathcal{H}_1 \) in (32) are independent of the preamble sequence. Thus, a solution of problem (36) optimizes the detection performance for all active devices with orthogonal preambles.

Optimization problem (36) cannot be solved directly because both constraint (36b) and the Marcum Q function are non-convex. Although the studies in [35] and [36] showed that \( Q_1(a, b) \) is monotonic and log-concave with respect to either \( a \) or \( b \), these results only hold when the other parameter is fixed. Thus, they are not applicable to (36) because parameters \( a \) and \( b \) depend on optimization variable \( w \).

Moreover, tight bounds and alternative representations of \( Q_1(a, b) \) were proposed in [37] and [38], respectively, which provide simplified analytical expressions of the Marcum Q function. However, these results do not lead to a tractable form for the optimization problem in (36).

\[^3\text{Alternatively, one could partition the coverage area into subareas and design the phase shifts for each subarea separately. These designs can be used to scan the coverage area over time. However, some active devices may be missed because only one subarea is illuminated at a time.}\]
Therefore, we propose two approximations of the Marcum Q function that facilitate solving (36). We denote the resulting approximate objective functions, which will be described in Sections IV-C and IV-D, respectively, as $J_k(W, q_t)$, $k \in \{1, 2\}$, where $W = WW^H \in \mathbb{C}^{U \times U}$ and $q_t \in \mathbb{Q}$ denote optimization variables.

### B. Reformulation to Min-Max SDP

Let $J_0(W, q_t)$ denote an approximation of the negative\(^4\) Marcum Q function in (36), where $W = WW^H$. Then, (36) can be written as follows

\[
\begin{align*}
\min_{W \in \mathbb{C}^{U \times U}} & \quad \max_{q_t \in \mathbb{Q}} \quad J_0(W, q_t) \\
\text{s.t.} & \quad W \succeq 0 \\
 & \quad |W|_{k \times u} = 1, \quad \forall u \in \{0, \ldots, U - 1\} \\
 & \quad \text{rank}(W) = 1,
\end{align*}
\]

(37a)

(37b)

(37c)

(37d)

which is the well-known semidefinite programming (SDP) representation of a min-max optimization problem with a unit-modulus optimization variable. Constraint (37d) guarantees that the optimal vector $w$ can be obtained from the decomposition of $W$ and (37c) ensures that the elements of $w$ have unit magnitude. Note that problem (37) is still non-convex due to constraint (37d), but we will show in Section V that this constraint can be replaced by adding a convex penalty term to the objective function.

### C. Lower Bound

As a first approximation, we adopt a lower bound of $Q_1(a, b)$, which maintains the general goal of the desired phase-shift design, i.e., maximizing a guaranteed probability of detection. It has been shown that [35], [39]

\[ Q(b + a) + Q(b - a) = Q_{0.5}(a, b) < Q_1(a, b) \]

(38)

for $a \geq 0$ and $b > 0$, where $Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^{\infty} e^{-\frac{t^2}{2}} dt$ denotes the Gaussian Q-function. Since $0 \leq Q(b + a) \leq Q(b - a)$ holds, we neglect $Q(b + a)$ in (38) and define the lower bound

\[ Q(b - a) < Q_1(a, b), \]

(39)

where

\[
\begin{align*}
a &= \sqrt{\frac{2P}{\text{Tr}(WM)} - \frac{2\sigma^2 \ln(P_F)}{\text{Tr}(WC)P + \sigma^2}} \\
b &= \sqrt{-\frac{2\sigma^2 \ln(P_F)}{\text{Tr}(WC)P + \sigma^2}}
\end{align*}
\]

(40)

(41)

are found from (35) with $M = h^\text{LoS} (h^\text{LoS})^H$. Note that (39) is tight\(^5\) if the LoS component of the channel is dominant compared to the NLoS component, because $Q(b - a) \approx Q_1(a, b)$ for $b \gg 1$ and $b \gg b - a$ [34].

\(^4\)Note the change of objective from max-min to min-max in (37).

\(^5\)The accuracies of the bounds in (38) and (39) are discussed in Section VI-D.

Of detection is maximized when the argument $b - a$ in (39) is minimized, leading to objective function

\[
J_1(W, q_t) = \frac{\sqrt{-2\sigma^2 \ln(P_F)} - 2P \text{Tr}(WM)}{\text{Tr}(WC)P + \sigma^2}.
\]

(42)

The fraction is avoided with the equivalent objective function

\[
J_1(W, q_t) = \ln \left( \frac{\sqrt{2P \text{Tr}(WM) - 2\sigma^2 \ln(P_F)}}{\sqrt{\text{Tr}(WC)P + \sigma^2}} \right)
\]

(43)

which is used in (37) to obtain the optimal phase-shift vector for the lower-bound approximation of (35).

From (43), we observe that minimizing $J_1(W, q_t)$ implies minimizing the contribution of the NLoS component and maximizing the contribution of the LoS component, which are reflected in the first and second term of (43), respectively. In addition, we note that solving (37) with $J_k(W, q_t)$ as objective function results in a phase-shift vector that depends on the noise power, the transmit power, the probability of false alarm, and the channel statistics.

### D. Objective Function for Strong LoS Path

The advantage of objective function (43) is that both the system parameters and the channel statistics are taken into account, which leads to phase-shift designs that accurately match a specific scenario. However, in practice, phase-shift designs that are applicable for different parameter sets may be preferable. For example, a design approach that is independent of the device’s transmit power allows a more versatile deployment of the RIS.

This can be accomplished by neglecting the scattered paths of the channel, which is a reasonable approximation for channels with a strong LoS component.\(^6\) Thus, by assuming $\text{Tr}(WC) \approx 0$, $J_1(W, q_t)$ becomes a monotonic function in $\text{Tr}(WM)$, which allows us to define the equivalent objective function

\[
J_2(W, q_t) = -\text{Tr}(WM).
\]

(44)

Similarly, it is straightforward to verify that $P_F$ in (35) is monotonic in $|w^H h^\text{LoS}|^2$ if $w^H C w \approx 0$. Objective function (44) only depends on the LoS component of the channel and is not affected by the transmit power, the noise power, and the desired probability of false alarm. Thus, designing the phase shifts based on $J_2(W, q_t)$ instead of $J_1(W, q_t)$ requires knowledge of fewer system parameters which facilitates a more versatile deployment. Moreover, as will be shown in Section VI, the detection performance obtained with phase shifts designed based on $J_1(W, q_t)$ and $J_2(W, q_t)$ is comparable in some cases. Furthermore, we note that $J_2(W, q_t)$ has been used as objective function in the conference version of this paper [1, Eq. (20)], cf. Remark 3.

\(^6\)The impact of neglecting the scattered paths is evaluated in Section VI-D.
E. Average Channel Gain

For RIS phase-shift design, besides the maximization of the probability of detection, the maximization of the average channel gain seems to be a reasonable objective [22], [23], [24]. The average channel gain is given by

\[
\mathbb{E}[|h|^2] = |w^H h\sigma|^2 + w^H C w = \text{Tr}(W (M + C)),
\]

which can be maximized for all locations \( q_t \in Q \) using objective function\(^7\)

\[
J_3(W, q_t) = -\text{Tr}(W (M + C))
\]  \hspace{1cm} (45)

in (37). We consider \( J_3(W, q_t) \) for the performance evaluation in Section VI and compare it to the results obtained with \( J_1(W, q_t) \) and \( J_2(W, q_t) \). Similar to \( J_2(W, q_t) \), \( J_3(W, q_t) \) does not depend on the transmit power, noise power, and probability of false alarm, and is only affected by the statistics of the channel.

V. OPTIMIZATION ALGORITHM

In the previous section, three objective functions for the min-max SDP in (37) were proposed. However, problem (37) cannot be solved directly because (37d) is a non-convex constraint. Therefore, we reformulate (37) in this section and exploit the MM principle to obtain a suboptimal phase-shift design for each objective function.

A. Problem Reformulation

Problem (37) can be equivalently rewritten as

\[
\begin{align*}
\min_{W \in C(u \times U), m \in \mathbb{R}} & \quad m + \rho (\|W\|_* - \|W\|_2) \\
\text{s.t.} & \quad W \succeq 0, \\
& \quad \|W\|_u \leq 1, \quad \forall u \in \{0, \ldots, U - 1\}, \\
& \quad J_k(W, q_t) \leq m, \quad \forall q_t \in Q,
\end{align*}
\]

where the max operation in (37a) is replaced by constraint (46d) and rank-one constraint (37d) is rewritten as a penalty term in (46a). More specifically, exploiting \( \|W\|_* - \|W\|_2 = 0 \) \( \Leftrightarrow \) \( \text{rank}(W) = 1 \), it has been shown that the solution of (46) is rank one if penalty factor \( \rho > 0 \) is sufficiently large [40].

In order to obtain optimized phase-shift designs based on (46), we examine the convexity of (46) for \( k \in \{1, 2, 3\} \). We note that \( J_2(W, q_t) \) and \( J_3(W, q_t) \) are convex functions, and that \( J_1(W, q_t) \) is the objective function in (46a) is in DC form. Thus, (46) can be solved using the MM principle, i.e., we apply convex upper bounds to the DC terms and iteratively solve the resulting optimization problem until convergence [41]. The upper bounds are found as follows.

**Lemma 2:** Let \( f(W) = f_{\text{cvx}}(W) + f_{\text{ccv}}(W) \) denote a function in DC form, i.e., \( f_{\text{cvx}}(W) \) and \( f_{\text{ccv}}(W) \) denote a convex and a concave function in \( W \geq 0 \), respectively. Then, \( f(W) \) is bounded as

\[
f(W) \leq \tilde{f}(W) = f_{\text{cvx}}(W) + f_{\text{ccv}}(W),
\]

where \( \tilde{f}(W) \) is a convex function in \( W \) and

\[
f_{\text{ccv}}(W) = f_{\text{ccv}}(W') + \text{Tr}(\nabla_W^H f_{\text{ccv}}(W') (W - W'))
\]  \hspace{1cm} (48)

denotes the first-order approximation of \( f_{\text{ccv}}(W) \) at \( W' \geq 0 \).

**Proof:** Since \( f_{\text{ccv}}(W) \) is a concave function and \( W \) and \( W' \) are from a convex set, the first-order approximation of \( f_{\text{ccv}}(W) \) at \( W' \) is a global overestimator of \( f_{\text{ccv}}(W) \), i.e., \( f_{\text{ccv}}(W) \leq f_{\text{ccv}}(W) [42] \). Adding \( f_{\text{ccv}}(W) \) to this inequality results in (47).

**Corollary 1:** Given \( W' \geq 0 \), a convex upper bound of the objective function in (46a) is given by

\[
m + \rho \text{Tr}
\left(
\begin{bmatrix}
I - v'v'^H
\end{bmatrix} W - \rho W'
\right)
\]

\[
\leq \frac{1}{2} \text{Tr}(W'C) + \rho \text{Tr}(v'v'^H W')
\]

\]  \hspace{1cm} (49)

where \( v' \) denotes the eigenvector that corresponds to the largest eigenvalue of \( W' \).

**Proof:** Using Lemma 2, we find

\[
\|W\|_* - \|W\|_2 \leq \|W\|_* - \|W'\|_2 - \text{Tr}(v'v'^H (W - W'))
\]  \hspace{1cm} (50)

because \( \nabla_W \|W\|_2 = v'v'^H \) [9], [43]. Using the identity \( \|\|_* = \text{Tr}() \) for positive semidefinite matrices and substituting the bound in (50) into (46a) results in (49).

**Corollary 2:** Given \( W' \geq 0 \), objective function \( J_1(W, q_t) \) is bounded as

\[
J_1(W, q_t) \leq \tilde{J}_1(W, W', q_t)
\]  \hspace{1cm} (51a)

\[
= -\ln \left( \sqrt{2P \text{Tr}(W'M)} - \sqrt{-2\sigma^2 \ln(P_F)} \right)
\]

\[
+ \ln \left( \text{Tr}(W'C) + \sigma^2 \right)
\]

\[
+ \frac{1}{2} \text{Tr}(W'C) + \rho \text{Tr}(v'v'^H W')
\]  \hspace{1cm} (51b)

**Proof:** Objective function \( J_1(W, q_t) \) can be written as

\[
J_1(W, q_t) = J_{1,\text{cvx}}(W, q_t) + J_{1,\text{ccv}}(W, q_t),
\]

where

\[
J_{1,\text{cvx}}(W, q_t) = -\ln \left( \sqrt{2P \text{Tr}(W'M)} - \sqrt{-2\sigma^2 \ln(P_F)} \right)
\]

\[
J_{1,\text{ccv}}(W, q_t) = \ln \left( \text{Tr}(W'C) + \sigma^2 \right)
\]

denote a convex and a concave function, respectively. The gradient of \( J_{1,\text{cvx}}(W, q_t) \) is given by

\[
\nabla_W J_{1,\text{cvx}}(W, q_t) = \frac{1}{2} \frac{CP}{\text{Tr}(W'C) + \sigma^2},
\]

which is found by applying the chain rule while taking the derivative of \( J_{1,\text{cvx}}(W, q_t) \) with respect to \( W \). Then, (51) follows from Lemma 2.

Now, we use Corollary 1 to replace the objective function in (46a) with its upper bound. In addition, we replace \( J_k(W, q_t) \) with \( \tilde{J}_k(W, W', q_t) \), where \( \tilde{J}_k(W, W', q_t) \) is given in Corollary 2.

\[
\tilde{J}_2(W, W', q_t) = J_2(W, q_t),
\]

and
Algorithm 1 Phase-Shift Optimization

Define $Q$, $k$, $ρ$, $ν$, and $w_0$:

\begin{align*}
& i ← 0; \\
& W_i, v_i, Ω_i ← w_i w_i^H, w_i, \max_{q_i ∈ Q} J_k(W_i, q_i); \text{repeat} \\
& \quad W', v' ← \text{solve}\problem{(56)}; \\
& \quad \Omega_{i+1} ← \text{decompose}(W_{i+1}); \\
& \quad i ← i + 1; \\
& \text{until } \left| \frac{Ω_{i} - Ω_{i-1}}{Ω_{i-1}} \right| ≤ ν; \\
& w_\text{opt} ← v_i.
\end{align*}

The resulting convex optimization problem for $k ∈ \{1, 2, 3\}$ is given as follows

\begin{align}
\min_{W ∈ O^U × U, m ∈ R^1} & m + \rho \operatorname{Tr}\left( (I - v'v'^H) W \right) \\
\text{s.t.} & W ≥ 0 \\
& [W]_{u×u} = 1, \quad ∀ u ∈ \{0, \ldots, U - 1\} \\
& \tilde{J}_k(W_i, q_i) ≤ m, \quad ∀ q_i ∈ Q,
\end{align}

where (56a) is obtained from (49) neglecting the terms not depending on $W$ or $m$.

Then, according to the MM principle, problem (56) is iteratively solved as follows. Given a feasible point $W_i = w_i w_i^H$ for the $i$th iteration of the algorithm, we set $v'^H = w_i$ and $W' = W_i$, and denote the solution of (56) as $W_{i+1}$.

As summarized in Algorithm 1, these steps are repeated until the objective function converges, i.e., the relative difference between the optimal values $Ω_i$ and $Ω_{i-1}$ is smaller than threshold $ν$.

Remark 6: We note that, with a slight modification of Algorithm 1, problem (37) can also be solved via semidefinite relaxation (SDR) and subsequent randomization [1], [44], [45]. Instead of employing rank penalty factor $ρ > 0$, one can relax the rank-one constraint by setting $ρ = 0$, which usually yields rank$(W_{i+1}) > 1$. Therefore, the decomposition of $W_{i+1}$ is replaced by Gaussian randomization. More specifically, $N_R$ random vectors are drawn from a complex Gaussian distribution with zero mean and covariance matrix $W_{i+1}$. Then, each vector is mapped to a feasible point of the original problem and the vector resulting in the lowest objective value is selected as the solution $v_{i+1}$, i.e., $W_{i+1} = v_{i+1}v_{i+1}^H$ is used as the initial value for the next iteration.

B. Convergence and Computational Complexity

Algorithm 1 follows the MM principle and iteratively solves (56), which tightens the upper bound of (46) in each iteration. Thus, the sequence $\{W_i, m_i\}_{i ∈ N}$ provides non-increasing sequences of objective values for (46) and for its equivalent formulation (37). Furthermore, these objective values converge to a stationary value because the objective functions of (46) and (37) are bounded below. As a result, the limit point of the sequence $\{W_i, m_i\}_{i ∈ N}$ obtained with Algorithm 1 converges to a stationary point of problem (37) [41].

The computational complexity of Algorithm 1 mainly depends on the complexity of solving problem (56) and the number of iterations required for convergence. In each iteration, problem (56) can be numerically solved with a worst-case complexity of $O\left( (Q + U)^4 \sqrt{U} \log \left( \frac{1}{ν} \right) \right)$, where $ν$ denotes the solution accuracy [46]. Thus, the computational complexity of Algorithm 1 is given by $O\left( N_I (Q + U)^4 \sqrt{U} \log \left( \frac{1}{ν} \right) \right)$, where $N_I$ denotes the number of iterations. As one can see, the complexity grows with the number of considered device locations. However, we note that relatively low numbers of $Q$ are sufficient to obtain highly accurate results, cf. Section VI-D. Moreover, the phase-shift design for device activity detection is an offline problem for which high computational complexity is less critical compared to online algorithms.

VI. PERFORMANCE EVALUATION

In this section, we evaluate the detection performance for different system parameters and compare the results obtained with objective functions $J_1(W, q_k), J_2(W, q_k)$, and $J_3(W, q_k)$. More specifically, we apply Algorithm 1 for $k ∈ \{1, 2, 3\}$, which results in three optimized phase-shift vectors $w_{\text{opt},1}^*, w_{\text{opt},2}^*, w_{\text{opt},3}^*$. Then, for each phase-shift vector, we use (35) to evaluate the minimum probability of detection across all locations within the coverage area, i.e., we plot $\min_{q_k ∈ Q} P_D(q_k)$. For convenience, we omit the arguments $(W, q_k)$ for the following discussion.

A. Baseline Phase-Shift Design

We also compare the performance of our proposed phase-shift designs with the quadratic phase-shift design in [1] and [7], which is an analytical phase-shift design for large coverage areas. In addition, this design is used for initialization of $w_0$ in Algorithm 1. Therefore, our evaluation will reveal the performance gain achieved by the additional effort of iteratively solving optimization problem (56).

B. System and Channel Parameters

The system parameters for the performance evaluation are summarized in Table I. Furthermore, since a suitable value of penalty factor $ρ$ depends on $k$, $P_{tx}$, $K$, etc., we select $ρ$ based on the set $\{1, 10, 100, 1000\}$ for each considered case.

Moreover, we study different channel conditions of the device-RIS link by varying the power ratio of the LoS and NLoS components, given by $K = \frac{\left|h(q_k)\right|^2}{\sum_{l=1}^{L} \sigma_l^2(q_k)}$. 

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TABLE I

| Parameter          | Value          |
|--------------------|----------------|
| $(x_s, y_s, z_s)$   | $(−10m, −30m, 30m)$ |
| $d_{tx}, \Psi(q_t)$| $(45, 8)$      |
| $\lambda$         | $0.1m$         |
| $\sigma^2$        | $−100dBm$      |

For simplicity, we assume equal variances $\bar{\sigma}^2 = \sigma^2(q_t)$, for all scattered paths, which results in $\bar{\sigma}^2 = |h(q_t)|^2/(KL)$. Furthermore, we assume $L = 2$ scattered paths and characterize their incident directions with angle $\alpha$ as shown in Fig. 2.

C. Comparison of Algorithm 1 and SDR Method

This section provides a comparison of the proposed Algorithm 1 with the SDR-based algorithm described in Remark 6. To this end, Fig. 3 shows numerical results for both schemes and objective functions $J_k$, $k \in \{1, 2, 3\}$, for different system parameters. The figure reveals that the proposed Algorithm 1 outperforms the SDR-based algorithm in most cases. We note that the SDR method can potentially provide good solutions, e.g., as observed in Fig. 3(b) for $J_2$, but has the following limitations due to the randomization step. The algorithm involves randomly generated vectors and their heuristic mapping to a feasible point of the original problem. As a result, convergence of the algorithm is not guaranteed, i.e., high detection performance cannot be obtained reliably [47]. In contrast, the proposed Algorithm 1 always converges to a stationary point and is the preferred option for practical systems.

D. Accuracy of Approximation

In this section, we evaluate the validity of the approximations required to find a solution of problem (36).

First, we examine the accuracy of the approximations that result in objective functions $J_1$ and $J_2$. Let $a_k$ and $b_k$ denote parameters $a$ in (40) and $b$ in (41), respectively, evaluated for $W_k = w_{opt,k} w_{opt,k}^H$, $k \in \{1, 2\}$. Then, we use the relative errors $\epsilon(J_k^1, q_t) = (Q(b_1 + a_1) + Q(b_1 - a_1))/Q(a_1(b_1) - 1)$ and $\epsilon(J_1, q_t) = Q(b_1 - a_1)/Q(a_1(b_1) - 1)$ to specify the accuracy of (38) and (39), respectively. Furthermore, we define $a_k = a_k|_{Tr(W_{k}C)}=0$ and $b_k = b_k|_{Tr(W_{k}C)}=0$ which represent $a_k$ and $b_k$, respectively, when the scattered paths are neglected. Thus, $Q_1(\tilde{a}_2, \tilde{b}_2)$ is the approximation of $Q_1(a_2, b_2)$ that results in $J_2$ and its relative error is given by $\epsilon(J_k, q_t) = Q_1(\tilde{a}_2, \tilde{b}_2)/Q_1(a_2, b_2) - 1$.

For the system parameters provided in Section VI-B and Table I, Fig. 4 shows the relative errors for different values of $K$, where we set $D_y = 20m$, $P_{tx} = −1dBm$, and $J_k(W, q_t), k \in \{1, 2, 3\}$. The randomization step of the SDR method employs $N_R = 1000$ randomly generated vectors.
\[ \alpha = 30^\circ. \] Here, we plot the largest relative error across the coverage area, i.e., for \( q_{i,+}^* = \arg \max_{q_i \in \mathcal{Q}} \epsilon(J_1^+, q_i) \), \( q_{1,1}^* = \arg \max_{q_i \in \mathcal{Q}} \epsilon(J_1, q_i) \), and \( q_{1,2}^* = \arg \max_{q_i \in \mathcal{Q}} \epsilon(J_2, q_i) \), respectively.

One can observe that the relative errors for \( J_1 \) remain below 0.02 for all considered values of \( K \). In addition, there is no noticeable difference between \( \epsilon(J_1^+, q_{i,+}) \) and \( \epsilon(J_1, q_{1,1}) \), which justifies using (39) instead of (38). Furthermore, we observe that the relative error for \( J_2 \) zero for large \( K \), but increases for low \( K \). However, for the performance evaluation, we consider RIS deployments that result in channels with a dominant LoS component \([48],[49]\).

Thus, assuming \( K \geq 3 \) dB, Fig. 4 confirms that \( J_1 \) and \( J_2 \) are accurate approximations with relative errors smaller than 0.06.

Finally, Fig. 5 studies the impact of sampling the coverage area for phase-shift design. Sampling is reasonable because the footprint of an RIS reflection beam always illuminates a small area around a target location. Thus, the continuous coverage area can be accurately covered when the sampled locations are sufficiently close together. In Fig. 5, a continuous coverage area of \( 20 \times 20 \) m is approximated by \( Q = 80^2 \) location samples, while the phase-shift design accounts for only \( Q' \in \{4^2, 8^2, 16^2, 16^2\} \) location samples. As one can see, the detection performance increases with \( Q' \), but saturates for \( Q' \geq 8^2 \), i.e., a relatively low number of location samples is sufficient to cover the considered area.

**E. Impact of Transmit Power**

The dependence of the detection performance on the transmit power is shown in Fig. 6. As expected, we observe an improvement of the detection performance for all phase-shift designs as the transmit power increases. Furthermore, for high transmit powers, the minimum probability of detection across the coverage area approaches 1 in all cases. In addition, Fig. 6 indicates that phase shifts designed based on \( J_1 \) and \( J_2 \) outperform those designed based on \( J_3 \) and the baseline quadratic design. The best performance is achieved with \( J_1 \), which improves the detection performance of the baseline quadratic design from 0.91 to 0.99 for \( P_{\text{tx}} = 0 \) dBm.

The differences in performance among the optimized phase-shift designs can be explained considering the different objective functions. More specifically, the detection performance in Fig. 6 depends on both the transmit power and the reflection gain of the RIS. For \( J_2 \) and \( J_3 \), the reflection gains are constant for all values of \( P_{\text{tx}} \) because both objective functions are independent of the transmit power. In contrast, the phase-shift design obtained for \( J_1 \) adapts to \( P_{\text{tx}} \), i.e., the reflection beam can be made narrower as the transmit power increases, which yields a better performance. Moreover, \( J_2 \) yields better results than \( J_3 \). Both objective functions maximize the power of the LoS paths but \( J_3 \) also enhances the power of the scattered paths, which leads to more variations in the effective end-to-end channel and worse detection performance.

**F. Impact of Scattering Strength**

The relation between the LoS and the NLoS components in the channel also plays an important role for phase-shift optimization, which is illustrated in Fig. 7. One can see that the detection performance increases with the value of \( K \) and that all optimized phase-shift designs converge for \( K \rightarrow \infty \) to the asymptotic performance of 0.984. This behavior can be explained with the reduced variations in the channel as \( K \) increases. For \( K \rightarrow \infty \), \( \mathbf{w}^H \mathbf{C} \mathbf{w} \rightarrow 0 \) and the channel becomes fully deterministic. In this case, \( J_1 \), \( J_2 \), and \( J_3 \) are equivalent.

For small values of \( K \), similar to Fig. 6, \( J_1 \) achieves the highest probability of detection, followed by \( J_2 \), \( J_3 \), and the baseline quadratic design.
G. Impact of Scattering Directions

In addition to the scattering strength, the incident directions of the scattered paths have an impact on the detection performance, too. In order to evaluate this dependence in more detail, Fig. 8 depicts the probability of detection for \( \alpha \in \{10^\circ, 20^\circ, 30^\circ\} \), which corresponds to scattering within the coverage area, near the edge of the coverage area, and with large distance to the coverage area, respectively, see Fig. 2. Interestingly, \( J_2 \) provides the best performance for \( \alpha = 10^\circ \), but \( J_1 \) is superior for \( \alpha \in \{20^\circ, 30^\circ\} \). This observation can be explained as follows.

Recall that \( J_1 \) is minimized by maximizing the power of the LoS paths and minimizing the power of the NLoS paths, which can be done concurrently and independently if both channel components are separable in the angular domain. For \( \alpha \in \{20^\circ, 30^\circ\} \), the separation is possible because the scattering is outside the coverage area. In this case, objective function \( J_1 \) results in a phase-shift design that suppresses the scattered paths, and thus achieves the best detection performance.

However, separation is not possible for \( \alpha = 10^\circ \). Consequently, there is a design conflict for \( J_1 \) because minimizing the power of the scattered paths also affects the reflection gain for some LoS paths. Therefore, the reflection gain for some device locations is reduced, which limits the minimum probability of detection across the coverage area.

In contrast, \( J_2 \) is independent of \( \alpha \), i.e., the phase-shift design considers the LoS paths to the coverage area only. As a result, the LoS and NLoS paths are equally reflected to the AP when the scattering is within the coverage area. Although this approach leads to more variations in the device-RIS channel, we observe in Fig. 8 that it provides the highest minimum probability of detection for \( \alpha = 10^\circ \). However, as \( \alpha \) increases, the best performance is achieved by \( J_1 \), which explicitly reduces the impact of the scattered paths.

H. Impact of Side Lobes

In order to highlight the difference between objective functions \( J_1 \) and \( J_2 \), Fig. 9 illustrates the reflection pattern of the RIS for the phase shifts designed with both \( J_1 \) and \( J_2 \), respectively, i.e., it displays the reflection gain \( |g(\Psi(q_t), \Psi(q_t))|^2 \) for all locations \( \{q_t | x_{q_t} = -10 m, -60 m < y_{q_t} < 20 m, 0 m < z_{q_t} < 60 m\} \). As in the schematic view in Fig. 2, the arrows in Fig. 9 indicate the incident directions of the two scattered paths and the rectangle marks the coverage area.

Figs. 9(a) and 9(b) show that both objective functions result in reflection patterns that fully illuminate the coverage area. However, there are differences between both patterns in the regions outside of the coverage area. More specifically, one can clearly see the zeros of the pattern in Fig. 9(a), whereas the zeros in Fig. 9(b) are less pronounced. These differences can be explained with objective functions \( J_1 \) and \( J_2 \). Since \( J_1 \) minimizes the impact of the scattered paths, the nulls of the resulting pattern are well aligned with the incident directions of the scattered paths. In Fig. 9(b), however, the scattered paths are neglected for the phase-shift optimization, which leads to more variations of the end-to-end channel gain compared to the pattern in Fig. 9(a). Hence, \( J_2 \) results in a lower detection performance than \( J_1 \).

I. Impact of Device Location

In order to investigate the detection performance for a specific device location, Fig. 10 shows the probability of detection for locations \( q_t \) on a circular arc in the second quadrant of the y-z plane, defined by angle \( \Theta(q_t) \in [-45^\circ, 45^\circ] \). The definition of \( \Theta(q_t) \) is equivalent to that of \( \alpha \), i.e., \( \Theta(q_t) = 0^\circ \) refers to the center of the coverage area at \(( -10 m, -30 m, 30 m) \), cf. Fig 2. One can see from Fig. 10 that the probability of detection for \( J_1 \) is similar across the entire coverage area, while \( \Theta(q_t) \) has a significant impact for the other phase-shift designs. Moreover, we observe that the detection performance significantly decreases for locations outside of

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the coverage area. Finally, the results suggest that the side lobes of the reflection pattern may also lead to good detection performance, e.g., as observed for $\Theta(q_t) \approx 40^\circ$.

### J. Impact of Area Size and RIS Size

As one can observe in Fig. 11, the size of the coverage area is also a limiting factor for the minimum guaranteed probability of detection. As expected, the figure shows that the detection performance decreases with increasing $D_y$ because the reflection gain of the RIS is distributed over a larger area. Moreover, Fig. 11 emphasizes the large gain that the optimized phase-shift designs achieve compared to the baseline quadratic design.

It is worth noting that phase shifts designed based on $J_1$ and $J_2$, respectively, provide almost the same performance for $D_y = 30$ m. In this case, the scatterers are close to the corner of the coverage area, i.e., the impact of the NLoS paths cannot be minimized by $J_1$ without reducing the reflection gain of the LoS paths.

Furthermore, we show the impact of the RIS size on the detection performance in Fig. 12. More specifically, we show the minimum probability of detection for different numbers of unit cells $U \in \{32, 48, 64\}$. Fig. 12 indicates that the detection performance improves when the size of the RIS increases, which is expected because more signal energy can be reflected to the AP with larger RISs. As $U$ changes from 32 to 64, we observe an improvement of at least 14% for the optimized phase-shift designs. Moreover, the differences between the design approaches remain the same, i.e., the best performance is achieved with $J_1$, followed by $J_2$, $J_3$, and the baseline quadratic design. The latter does not yield a large gain as $U$ increases because the phase shifts are not specifically designed to maximize the minimum probability of detection. Consequently, the illumination of some parts of the coverage area may not be improved with larger RIS size, which limits the minimum detection performance across the coverage area.

### K. Receiver Operating Characteristic

Finally, Fig. 13 shows the receiver operating characteristic of our proposed detector. For $P_F \geq 0.1$, one can see that all phase-shift designs result in a high probability of detection across the coverage area, i.e., $\min_{q_t \in Q} P_D(q_t) \geq 0.9$. Moreover, for $P_F \geq 0.01$, the detection performance is still higher than 0.7. In addition, the figure indicates that the order among the phase-shift designs regarding detection performance is independent of the probability of false alarm. More specifically, objective function $J_1$ results in the highest detection performance for all values of $P_F$, followed by $J_2$, $J_3$, and the baseline quadratic design.

### VII. Conclusion

This paper studied device activity detection for GF uplink transmission in RIS-assisted communication systems, where the RIS was deployed to cover a specific area. In order to
optimally design the phase shifts of the RIS, we employed GLRT for device activity detection and showed that the resulting probability of detection can be expressed in terms of the Marcum Q function. Furthermore, we formulated an optimization problem for the RIS phase shifts for maximization of the minimum probability of detection across the coverage area. The non-convexity of the optimization problem was tackled by applying the MM principle and using two approximations of the Marcum Q function. Based on a lower bound of the Marcum Q function, the first approximation resulted in the best detection performance in most cases because all system parameters and the channel statistics are taken into account for phase-shift optimization. For the second approximation, we neglected the scattered paths of the channel for the phase-shift optimization and showed that a similar performance as for the first approximation is achieved when the LoS paths of the channel are dominant or when the NLoS paths and LoS paths of the channel share the same incident angles. In addition, the second approximation resulted in a versatile objective function for phase-shift optimization because it does not depend on system parameters such as transmit power, noise power, and probability of false alarm. Finally, our performance evaluation revealed that maximizing the average channel gain is not a suitable phase-shift design criterion for RIS-assisted device activity detection. In particular, this approach increases the variance of the end-to-end channel, which has a negative impact on the probability of detection.

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