

RIScatter: Unifying Backscatter Communication and Reconfigurable Intelligent Surface

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Abstract—Backscatter Communication (BackCom) nodes harvest energy from and modulate information over external electromagnetic waves. Reconfigurable Intelligent Surface (RIS) adapts its phase shift response to alter channel strength in specific directions. In this paper, we show how those two different technologies (and their derivatives) can be unified into one architecture called RIScatter. RIScatter consists of dispersed or co-located scatter nodes, whose reflection states are adapted to partially modulate their information and partially engineer the wireless channel. The key is to render the probability distribution of reflection states as a joint function of the information source, Channel State Information (CSI), and relative priority of coexisting links. This enables RIScatter to softly bridge BackCom and RIS; reduce to either under specific distribution; or evolve in a mixed form for heterogeneous traffic control and universal hardware design. We also propose a low-complexity Successive Interference Cancellation (SIC)-free receiver that effectively exploits the properties of RIScatter. For a single-user multi-node network, we characterize the achievable primary-(total-)backscatter rate region by optimizing the input distribution at scatter nodes, the active beamforming at the Access Point (AP), and the energy decision regions at the user. Simulations demonstrate RIScatter nodes can recycle surrounding radios for backscatter modulation and passive beamforming.

Index Terms—Backscatter communication, reconfigurable intelligent surface, active-passive coexisting network, input distribution design, SIC-free receiver.

I. INTRODUCTION

FUTURE wireless network is envisioned to provide high throughput, uniform coverage, pervasive connectivity, heterogeneous control, and cognitive intelligence for trillions of low-power devices. Backscatter Communication (BackCom) separates a transmitter into a Radio-Frequency (RF) carrier emitter with power-hungry elements (e.g., synthesizer and amplifier) and an information-bearing node with power-efficient components (e.g., harvester and modulator) [1]. The receiver (reader) can be either co-located or separated with the carrier emitter, known as Monostatic BackCom (MBC) and Bistatic BackCom (BBC) in Fig. 1(a) and 1(b), respectively. Relevant applications such as Radio-Frequency Identification (RFID) [2], [3] and passive sensor network [4], [5] have been extensively researched, standardized, and commercialized to embrace the Internet of Everything (IoE). However, conventional backscatter nodes only respond when externally inquired by a nearby reader. Ambient Backscatter Communication (AmBC) in Fig. 1(c) was proposed a decade ago where battery-free nodes recycle ambient signals (e.g., radio, television and Wi-Fi)

to harvest energy and establish connections [6]. It does not require dedicated power source, carrier emitter, or frequency spectrum, but the backscatter decoding is subject to the strong interference from the primary (legacy) link. To tackle this, cooperative AmBC [7] employs a co-located receiver to decode both coexisting links and the concept was further refined as Symbiotic Radio (SR) in Fig. 1(d) [8]. Specifically, the active transmitter generates RF wave carrying primary information, the passive node creates a rich-scattering environment and rides its own information, and the co-located receiver cooperatively decodes both links. In those BackCom applications, the scatter node is considered as an *information source* and the reflection pattern depends exclusively on the information symbol. On the other hand, Reconfigurable Intelligent Surface (RIS) in Fig. 1(e) is a smart signal reflector with numerous passive elements of adjustable phase shifts. It customizes the wireless environment for signal enhancement, interference suppression, scattering enrichment, and/or non-line-of-sight bypassing [9]. Each RIS element is considered as a *channel shaper* and the reflection pattern depends exclusively on the Channel State Information (CSI).

As a special case of Cognitive Radio (CR), active and passive transmissions coexist and interplay in AmBC and SR. Such a coexistence is classified into commensal (overlay), parasitic (underlay), and competitive (interfering) paradigms, and their achievable rate and outage performance were investigated in [10], [11]. For the co-located cooperative receiver, the Bit Error Rate (BER) performance of Maximum-Likelihood (ML), linear, and Successive Interference Cancellation (SIC) detectors are derived over flat fading channels [7]. However, the work assumed equal symbol duration and perfect synchronization for primary and backscatter links. Importantly, active-passive coexisting networks have three special and important properties:

- 1) Primary and backscatter symbols are superimposed by *double modulation* (i.e., multiplication coding);
- 2) Backscatter signal strength is much weaker than primary due to the *double fading* effect;
- 3) The spreading factor (i.e., backscatter symbol duration over primary) is usually large¹.

The second property motivated [7], [8], [10], [11], [13]–[19] to view SR as a multiplicative Non-Orthogonal Multiple Access (NOMA) and perform SIC from primary to backscatter link. During primary decoding, the backscatter signal can be modelled as channel uncertainty or multiplicative interference when the spreading factor is large or small, respectively.

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¹The load-switching interval of low-power backscatter modulators is usually 0.1 to 10 μ s [12], accounting for a typical spreading factor between 10 and 10^3 .

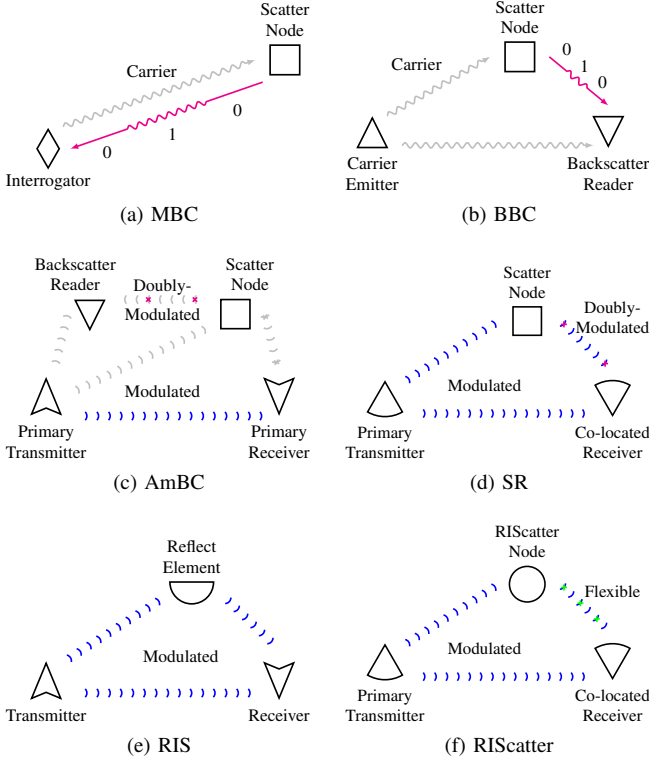


Fig. 1. Illustration of scattering applications. The blue flow(s) constitutes the primary link while the magenta/green flow denotes the backscatter link.

Decoding each backscatter symbol also requires multiple SIC followed by a Maximal Ratio Combining (MRC) over primary blocks, which is operation-intensive and CSI-sensitive. When the spreading factor is sufficiently large, the primary achievable rate under semi-coherent detection² asymptotically approaches its coherent counterpart and both links are decoded interference-free [13]. However, this severely limits the backscatter throughput and requires numerous SIC per backscatter symbol.

On the other hand, static RIS design with fixed reflection pattern per channel block has been extensively studied in wireless communication, sensing, and power literature [20]–[25]. Dynamic RIS performs time sharing between different phase shifts and introduces artificial channel diversity within each channel block. It was first proposed to fine-tune the Orthogonal Frequency-Division Multiplexing (OFDM) resource blocks [26] then extended to the downlink power and uplink information phases of Wireless Powered Communication Network (WPCN) [27]–[29]. However, dynamic RIS carries *no* additional information since the reflection state at each time slot is known to the receiver. RIS can also be used as an information source and prototypes have been developed for Phase Shift Keying (PSK) [30] and Quadrature Amplitude Modulation (QAM) [31]. From an information-theoretic perspective, the authors of [32] reported that joint transmitter-RIS encoding achieves the capacity of RIS-aided finite-input channel and using RIS as a naive passive beamformer to maximize the receive Signal-to-Noise Ratio (SNR) is generally suboptimal.

²In this paper, semi-coherent detection refers to the primary/backscatter decoding with known CSI and unknown backscatter/primary symbols.

This inspired RIS-empowered BackCom [33]–[42] to combine passive beamforming and backscatter modulation in the overall reflection pattern. In particular, *symbol level precoding* maps the information symbols to the optimized RIS coefficient sets [33], [34], *overlay modulation* superposes the information symbols over a common auxiliary matrix [35]–[38], *spatial modulation* switches between the reflection coefficient sets that maximize SNR at different receive antennas [39]–[41], and *index modulation* employs dedicated reflection elements (resp. information elements) for passive beamforming (resp. backscatter modulation) [42]. However, those joint designs incur advanced hardware architecture and high optimization complexity. Relevant literature also considers either Gaussian codebook [10], [11], [13]–[17], [37] that is impractical for low-power nodes or finite equiprobable inputs [7], [8], [18], [19], [33]–[36], [38]–[42] that does not fully exploit the CSI and properties of active-passive coexisting networks. Those problems are addressed in this paper and the contributions are summarized below.

First, we propose RIScatter as a novel protocol that unifies BackCom and RIS by adaptive reflection state (backscatter input) distribution design. The concept is shown in Fig. 1(f) where one or more RIScatter nodes ride over an active transmission and simultaneously modulate their information and engineer the wireless channel. A co-located receiver cooperatively decodes both coexisting links and each reflection state simultaneously acts as information and passive beamforming codewords. The reflection pattern of each node is semi-randomly chosen with the guidance of input distribution as a joint function of the information source, CSI, and Quality of Service (QoS)³. Such an adaptive channel coding boils down to the degenerate distribution of RIS when the primary link is prioritized, and outperforms the uniform distribution of BackCom (by accounting the CSI) when the backscatter link is prioritized. Joint and independent encoding are available when multiple RIScatter nodes are co-located and dispersed, respectively. Table I compares RIScatter to BackCom and RIS. However, two major challenges for RIScatter are the practical receiver and input distribution design. This is the first paper to unify BackCom and RIS from the perspective of input distribution.

Second, we address the first challenge and propose a practical receiver that semi-coherently decodes the backscatter information, recovers the reflection pattern, and coherently decodes the primary link. We consider backscatter energy detection and formulate a Discrete Memoryless Multiple Access Channel (DMMAC) over disjoint decision regions. Thanks to the double modulation and symbol-level passive precoding, the semi-coherent backscatter decoding is essentially part of channel training. Once the backscatter information is successfully decoded, its contribution can be modelled within composite channel as dynamic passive beamforming (rather than re-precoded and cancelled). Such a sequential decoding transforms backscatter modulation into dynamic passive beamforming using only one re-encoding and one energy level comparison per backscatter block. It is also suitable for arbitrary input distribution and spreading factor, which significantly improves backscatter throughput. This

³QoS refers to the relative priority of the primary link.

TABLE I
COMPARISON OF SCATTERING APPLICATIONS

	MBC/BBC	AmBC	SR (large spreading factor)	RIS	RIScatter
Information link(s)	Backscatter	Coexisting	Coexisting	Primary	Coexisting
Primary signal on backscatter decoding	Carrier	Multiplicative interference	Spreading code	—	Energy uncertainty
Backscatter signal on primary decoding	—	Multiplicative interference	CSI uncertainty	Passive beamforming	Dynamic passive beamforming
Cooperative devices	—	No	Primary transmitter and co-located receiver	—	Primary transmitter, scatter nodes, and co-located receiver
Sequential decoding	—	No	Primary-to-backscatter, SIC and MRC	—	Backscatter-to-primary, no SIC/MRC
Reflection pattern depends on	Information source	Information source	Information source	CSI	Information source, CSI, and QoS
Reflection state distribution	Equiprobable	Equiprobable	Equiprobable or Gaussian	Degenerate	Flexible
Load-switching speed	Fast	Slow	Slow	Quasi-static	Arbitrary

is the first paper to consider practical backscatter-primary decoding scheme to exploit backscatter modulation as dynamic passive beamforming at the co-located receiver.

Third, we address the second challenge and consider a single-user multi-node Multiple-Input Single-Output (MISO) scenario. We characterize the achievable primary-(total-)backscatter rate region by optimizing the input distribution at RIScatter nodes, the active beamforming at the Access Point (AP), and the energy decision regions at the user under different QoS. A Block Coordinate Descent (BCD) algorithm is proposed where the Karush-Kuhn-Tucker (KKT) input distribution is numerically evaluated by limit of sequences, the active beamforming is optimized by Projected Gradient Ascent (PGA), and the decision regions are refined by existing sequential quantizer for Discrete Memoryless Thresholding Channel (DMTC). Uniquely, we consider CSI, QoS, and backscatter constellation in the optimization and the input distribution result is applicable to general detection schemes. This is also the first paper to reveal the importance of backscatter input distribution and decision region designs in active-passive coexisting networks.

Notations: Italic, bold lower-case, and bold upper-case letters denote scalars, vectors and matrices, respectively. $\mathbf{0}$ and $\mathbf{1}$ denote zero and one array of appropriate size, respectively. $\mathbb{I}^{x \times y}$, $\mathbb{R}_+^{x \times y}$, and $\mathbb{C}^{x \times y}$ denote the unit, real nonnegative, and complex spaces of dimension $x \times y$, respectively. j denotes the imaginary unit. $\text{diag}(\cdot)$ returns a square matrix with the input vector on its main diagonal and zeros elsewhere. $\text{card}(\cdot)$ returns the cardinality of a set. $\log(\cdot)$ denotes logarithm of base e . $(\cdot)^*$, $(\cdot)^T$, $(\cdot)^H$, $|\cdot|$, and $\|\cdot\|$ denote the conjugate, transpose, conjugate transpose (Hermitian), absolute value, and Euclidean norm operators, respectively. $(\cdot)^{(r)}$ and $(\cdot)^*$ denote the r -th iterated and optimal results, respectively. The distribution of a Circularly Symmetric Complex Gaussian (CSCG) random variable with zero mean and variance σ^2 is denoted by $\mathcal{CN}(0, \sigma^2)$, and \sim means “distributed as”.

II. RIScatter

A. Principles

RF wave scattering or reflecting are often manipulated by passive antennas or programmable metamaterial [43]. The former receives the impinging signals and reradiates some back to the space, while the latter reflects at the space-cell boundary and mainly applies a phase shift. In the scattered signal, the structural mode component depends on the scatterer geometry and material. It is usually modelled as a DC offset [1] or part of environment multipath [44]. On the other hand, the antenna mode component depends on the impedance mismatch and is widely exploited in scattering applications. For an antenna (resp. metamaterial) scatterer with M reflection states, the reflection coefficient at state $m \in \mathcal{M} \triangleq \{1, \dots, M\}$ is [43], [45]

$$\Gamma_m = \frac{Z_m - Z^*}{Z_m + Z}, \quad (1)$$

where Z_m is the antenna load (resp. metamaterial cell) impedance at state m , and Z is the antenna input (resp. medium characteristic) impedance. Specifically,

- **BackCom:** The scatterer is an information source with random reflection pattern over time. The reflection coefficient is used merely an information codeword [46]

$$\Gamma_m = \alpha_m \frac{c_m}{\max_{m'} |c_{m'}|}, \quad (2)$$

where $\alpha_m \in \mathbb{I}$ is the amplitude scattering ratio and c_m is the constellation point.

- **RIS:** The scatterer is a channel shaper with deterministic reflection pattern over time. The reflection coefficient is used merely a passive beamforming codeword [20]

$$\Gamma_m = \alpha_m \exp(j\theta_m), \quad (3)$$

where θ_m is the phase shift.⁴

RIScatter generalizes BackCom and RIS from a probabilistic perspective. Each reflection coefficient simultaneously acts

⁴It is commonly assumed $\alpha_m \ll 1$ in BackCom and $\alpha_m = 1$ in RIS.



Fig. 2. Input distribution and reflection pattern of scattering applications. “PB”, “BB”, and “CB” refer to primary symbol block, backscatter symbol block, and channel block, respectively. Shadowing means presence of primary link. In this example, the optimal passive beamformer corresponds to state 2. The spreading factor is 4 for RIScatter and 8 for AmBC/SR. BackCom and RIS can be viewed as extreme cases of RIScatter, where the input distribution boils down to uniform and degenerate, respectively.

as an information codeword and a passive beamforming codeword. As shown in Fig. 2, RIScatter nodes semi-randomly choose reflection states according to an input distribution, which strikes a balance between backscatter modulation and passive beamforming.

Remark 1. Unlike dynamic RIS that simply performs a time sharing between reflection states, RIScatter conveys additional information by randomizing the reflection pattern over time while still guaranteeing the probability of occurrence of each state. Upon successful backscatter detection, the impact of RIScatter nodes on the primary link can be modelled as dynamic passive beamforming.

RIScatter nodes can be implemented, for example, by adding an integrated receiver [47] and adaptive encoder [48] to off-the-shelf passive RFID tags. The block diagram, equivalent circuit, and scatter model are illustrated in Fig. 3. To exploit the benefits of RIScatter, we also propose a low-complexity receiver that semi-coherently decodes the backscatter link, recovers the reflection pattern, and coherently decodes the primary link. The detail will be covered in Section II-B.

B. System Model

As shown in Fig. 4, we consider a RIScatter network where a Q -antenna AP serves a single-antenna user and K nearby dispersed or co-located RIScatter nodes. All nodes have M available reflection states. In the primary point-to-point system, the AP transmits information to the user over a multipath channel⁵ enhanced by RIScatter nodes. In the backscatter

multiple access system, the AP acts as carrier emitter, the RIScatter nodes modulate over scattered signal, and the user jointly decodes all node messages.⁶ For simplicity, we consider a quasi-static block fading model and focus on a specific channel block where the CSI remains constant. Denote the AP-user direct channel as $\mathbf{h}_D^H \in \mathbb{C}^{1 \times Q}$, the AP-node $k \in \mathcal{K} \triangleq \{1, \dots, K\}$ forward channel as $\mathbf{h}_{F,k}^H \in \mathbb{C}^{1 \times Q}$, the node k -user backward channel as $\mathbf{h}_{B,k}$, and the cascaded AP-node k -user channel as $\mathbf{h}_{C,k}^H \triangleq \mathbf{h}_{B,k} \mathbf{h}_{F,k}^H \in \mathbb{C}^{1 \times Q}$. We assume the direct and cascaded CSI are available at the AP and user⁷.

Let $\alpha_k \in \mathbb{I}$ be the amplitude scattering ratio of node k , $x_k \in \mathcal{X} \triangleq \{c_1, \dots, c_M\}$ be the coded backscatter symbol of node k , and $x_K \triangleq (x_1, \dots, x_K)$ be the backscatter symbol tuple of all nodes. As a sequence of double modulation, the composite channel is a function of backscatter symbol tuple⁸

$$\mathbf{h}^H(x_K) \triangleq \mathbf{h}_D^H + \sum_k \alpha_k \mathbf{h}_{C,k}^H x_k \quad (4a)$$

$$= \mathbf{h}_D^H + \mathbf{x}^H \text{diag}(\boldsymbol{\alpha}) \mathbf{H}_C, \quad (4b)$$

where $\boldsymbol{\alpha} \triangleq [\alpha_1, \dots, \alpha_K]^T \in \mathbb{I}^K$, $\mathbf{x} \triangleq [x_1, \dots, x_K]^H \in \mathcal{X}^K$, and $\mathbf{H}_C \triangleq [\mathbf{h}_{C,1}, \dots, \mathbf{h}_{C,K}]^H \in \mathbb{C}^{K \times Q}$. Within one backscatter block, the signal received by the user at primary block $n \in \mathcal{N} \triangleq \{1, \dots, N\}$ is

$$y[n] = \mathbf{h}^H(x_K) \mathbf{w} s[n] + v[n], \quad (5)$$

where $\mathbf{w} \in \mathbb{C}^Q$ is the active beamformer satisfying $\|\mathbf{w}\|^2 \leq P$, P is the average transmit power budget, $s \sim \mathcal{CN}(0, 1)$ is the primary symbol, and $v \sim \mathcal{CN}(0, \sigma_v^2)$ is the Additive White Gaussian Noise (AWGN) with variance σ_v^2 .

Let $m_k \in \mathcal{M} \triangleq \{1, \dots, M\}$ be the reflection state index of node k , and $m_K \triangleq (m_1, \dots, m_K)$ be the state index tuple of all nodes. The backscatter symbol x_k (resp. symbol tuple x_K) is a random variable that takes value x_{m_k} (resp. value tuple x_{m_K}) with probability $p(x_{m_k})$ (resp. $p(x_{m_K})$).

Remark 2. Dispersed RIScatter nodes encode independently such that

$$p(x_{m_K}) = \prod_k p(x_{m_k}). \quad (6)$$

When the nodes are co-located, they can jointly encode by designing $p(x_{m_K})$ directly.

Let $z = \sum_n |y[n]|^2$ be the receive energy per backscatter block. When x_{m_K} is transmitted, the receive signal y follows CSCG distribution $\mathcal{CN}(0, \sigma_{m_K}^2)$ with variance

$$\sigma_{m_K}^2 = |\mathbf{h}^H(x_{m_K}) \mathbf{w}|^2 + \sigma_v^2, \quad (7)$$

and z follows Gamma distribution with conditional Probability Density Function (PDF)

$$f(z|x_{m_K}) = \frac{z^{N-1} \exp(-z/\sigma_{m_K}^2)}{\sigma_{m_K}^{2N} (N-1)!}. \quad (8)$$

⁵It is assumed the primary symbol duration is much longer than multipath delay spread (no inter-symbol interference).

⁶It is assumed the signal going through two or more RIScatter nodes is too weak to be received by the user.

⁷The cascaded CSI can be estimated by sequential [50]–[52] or parallel [53] approaches for dispersed nodes, or group-based [54] or hierarchical [55] approaches for co-located nodes.

⁸(4a) and (4b) are often used in BackCom and RIS literature, respectively.



Fig. 3. Block diagram, equivalent circuit, and scatter model of a RIScatter node. The solid and dashed vectors represent signal and energy flows. The scatter antenna behaves as a constant power source, where the voltage V_0 and current I_0 are introduced by incident electric field \vec{E}_I and magnetic field \vec{H}_I [49].

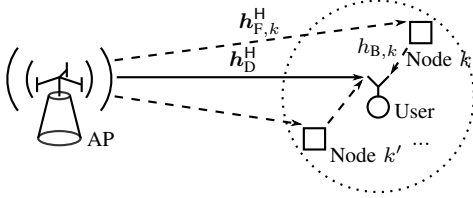


Fig. 4. A single-user multi-node RIScatter network.

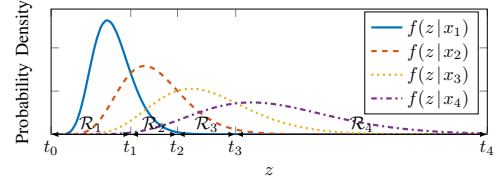


Fig. 5. PDF of the receive energy per backscatter block conditioned on different reflection state.

Remark 3. We have assumed Gaussian codebook for the primary source and finite support for the backscatter nodes, since they are relatively practical and widely adopted in relevant literatures. The proposed framework is extendable to non-Gaussian primary source, and the conditional PDF (8) can be approximated using Central Limit Theorem (CLT) for large N .

The user first jointly decodes the backscatter message of all nodes using a low-complexity energy detector.⁹ The energy detector formulates a DMTC of size $M^K \times M^K$.

Remark 4. The capacity-achieving decision region design for DMTC with non-binary inputs in arbitrary distribution remains an open issue. It was proved deterministic detectors can be rate-optimal, but non-convex regions (comprise non-adjacent partitions) are generally required and the optimal number of thresholds is unknown [57], [58]. Next, we restrict the energy detector to convex deterministic decision regions and consider sequential threshold design.

Let $L = M^K$ be the number of decision regions. Sort $\{\sigma_{m_K}^2\}$ in ascending order and denote the result sequence as $\sigma_1^2, \dots, \sigma_L^2$. With sequential thresholding, the decision region of backscatter symbol tuple $l \in \mathcal{L} = \{1, \dots, L\}$ is¹⁰

$$\mathcal{R}_l \triangleq [t_{l-1}, t_l), \quad 0 \leq t_{l-1} \leq t_l, \quad (9)$$

where t_l is the decision threshold between hypotheses x_l and x_{l+1} . An example is shown in Fig. 5.

⁹The reliability of the energy detector is improved by the adaptive input distribution and thresholding design. With high-order modulation or large number of scatter nodes, the reliability can be further enhanced by increasing the spreading factor or using error correction codes with lower code-rate. In practice, users can decode backscatter nodes ranging from a few to hundreds of meters in the presence of noise and interference, and the backscatter throughput can reach few Kbps to tens of Mbps [56].

¹⁰ m_K and l are one-to-one and used interchangeably in the following context.

When the threshold vector $\mathbf{t} \triangleq [t_0, \dots, t_L]^T \in \mathbb{R}_+^{L+1}$ is given, we can formulate a DMMAC with transition probability from input x_{m_K} to output $\hat{x}_{m'_K}$ as

$$q(\hat{x}_{m'_K} | x_{m_K}) = \int_{\mathcal{R}_{m'_K}} f(z | x_{m_K}) dz. \quad (10)$$

The backscatter mutual information is

$$I_B(x_K; \hat{x}_K) = \sum_{m_K} p(x_{m_K}) I_B(x_{m_K}; \hat{x}_K), \quad (11)$$

where $I_B(x_{m_K}; \hat{x}_K)$ is the backscatter information function

$$I_B(x_{m_K}; \hat{x}_K) \triangleq \sum_{m'_K} q(\hat{x}_{m'_K} | x_{m_K}) \log \frac{q(\hat{x}_{m'_K} | x_{m_K})}{p(\hat{x}_{m'_K})}. \quad (12)$$

Once the backscatter information is successfully decoded, the user recovers the exact reflection pattern, determines the composite channel by (4), and coherently decodes the primary link. The primary mutual information is

$$I_P(s; y | x_K) = \sum_{m_K} p(x_{m_K}) I_P(s; y | x_{m_K}), \quad (13)$$

where $I_P(s; y | x_{m_K})$ is the primary information function

$$I_P(s; y | x_{m_K}) \triangleq \log \left(1 + \frac{|\mathbf{h}^H(x_{m_K}) \mathbf{w}|^2}{\sigma_v^2} \right). \quad (14)$$

III. RATE-REGION CHARACTERIZATION

With a slight abuse of notation, we define the weighed sum mutual information and information function as

$$I(x_K) \triangleq \rho I_P(s; y | x_K) + (1 - \rho) I_B(x_K; \hat{x}_K), \quad (15)$$

$$I(x_{m_K}) \triangleq \rho I_P(s; y | x_{m_K}) + (1 - \rho) I_B(x_{m_K}; \hat{x}_K), \quad (16)$$

where $\rho \in \mathbb{I}$ is the QoS. To obtain the achievable primary-(total-)backscatter rate region, we consider the weighted sum

mutual information maximization problem with independent encoding at all nodes¹¹

$$\max_{\{\mathbf{p}_k\}_{k \in \mathcal{K}}, \mathbf{w}, \mathbf{t}} I(x_{\mathcal{K}}) \quad (17a)$$

$$\text{s.t.} \quad \mathbf{1}^\top \mathbf{p}_k = 1, \quad \forall k, \quad (17b)$$

$$\mathbf{p}_k \geq \mathbf{0}, \quad \forall k, \quad (17c)$$

$$\|\mathbf{w}\|^2 \leq P, \quad (17d)$$

$$t_{l-1} \leq t_l, \quad \forall l, \quad (17e)$$

$$\mathbf{t} \geq \mathbf{0}, \quad (17f)$$

where $\mathbf{p}_k = [p(x_{1_k}), \dots, p(x_{M_k})]^\top \in \mathbb{I}^M$ is the input distribution of node k . Problem (17) generalizes BackCom by allowing CSI- and QoS-adaptive input distribution and decision region design. On the other hand, it also relaxes the feasible domain of discrete RIS phase shift selection problem from vertices of M -dimensional probability simplex to the simplex itself. The original problem is highly non-convex and we propose a BCD algorithm that iteratively updates $\{\mathbf{p}_k\}_{k \in \mathcal{K}}$, \mathbf{w} and \mathbf{t} .

A. Input Distribution

For any given \mathbf{w} and \mathbf{t} , we can formulate a DMMAC by (10) and simplify (17) to

$$\max_{\{\mathbf{p}_k\}_{k \in \mathcal{K}}} I(x_{\mathcal{K}}) \quad (18a)$$

$$\text{s.t.} \quad (17b), (17c), \quad (18b)$$

which involves the product term (6) and is generally non-convex (unless $K=1$). Following [59], we first recast the KKT conditions to their equivalent forms, then propose a numerical method that guarantees those conditions on convergence of sequences.

Proposition 1. *The KKT optimality conditions for problem (18) are equivalent to, $\forall k, m_k$,*

$$I_k^*(x_{m_k}) = I^*(x_{\mathcal{K}}), \quad \text{if } p^*(x_{m_k}) > 0, \quad (19a)$$

$$I_k^*(x_{m_k}) \leq I^*(x_{\mathcal{K}}), \quad \text{if } p^*(x_{m_k}) = 0, \quad (19b)$$

where $I_k(x_{m_k})$ is the weighted sum marginal information

$$I_k(x_{m_k}) = \sum_{m_{\mathcal{K} \setminus \{k\}}} p(x_{m_{\mathcal{K} \setminus \{k\}}}) I(x_{m_{\mathcal{K}}}). \quad (20)$$

Proof. Please refer to Appendix A. \square

For each RIScatter node, (19a) suggests each probable state should produce the same marginal information (averaged over all states of other nodes), while (19b) suggests any state with potentially less marginal information should not be used.

Proposition 2. *For any strictly positive initializer $\{\mathbf{p}_k^{(0)}\}_{k \in \mathcal{K}}$, the KKT input probability of node k at state m_k is given by the converging point of the sequence*

$$p^{(r+1)}(x_{m_k}) = \frac{p^{(r)}(x_{m_k}) \exp\left(\frac{\rho}{1-\rho} I_k^{(r)}(x_{m_k})\right)}{\sum_{m'_k} p^{(r)}(x_{m'_k}) \exp\left(\frac{\rho}{1-\rho} I_k^{(r)}(x_{m'_k})\right)}, \quad (21)$$

¹¹Joint encoding over multiple nodes can be viewed as its special case with an augmented source.

Algorithm 1: KKT Input Distribution Evaluation by Limits of Sequence

Input: $K, N, \mathbf{h}_D^H, \mathbf{H}_C, \boldsymbol{\alpha}, \mathcal{X}, \sigma_v^2, \rho, \mathbf{w}, \mathbf{t}, \epsilon$

Output: $\{\mathbf{p}_k^*\}_{k \in \mathcal{K}}$

- 1: Set $\mathbf{h}^H(x_{m_{\mathcal{K}}}), \forall m_{\mathcal{K}}$ by (4)
- 2: $\sigma_{m_{\mathcal{K}}}^2, \forall m_{\mathcal{K}}$ by (7)
- 3: $f(z|x_{m_{\mathcal{K}}}), \forall m_{\mathcal{K}}$ by (8)
- 4: $q(\hat{x}_{m'_k}|x_{m_{\mathcal{K}}}), \forall m_{\mathcal{K}}, m'_k$ by (10)
- 5: Initialize $r \leftarrow 0$
- 6: $\mathbf{p}_k^{(0)} > \mathbf{0}, \forall k$
- 7: Get $p^{(r)}(x_{m_{\mathcal{K}}}), \forall m_{\mathcal{K}}$ by (6)
- 8: $I^{(r)}(x_{m_{\mathcal{K}}}), \forall m_{\mathcal{K}}$ by (12), (14), (16)
- 9: $I_k^{(r)}(x_{m_k}), \forall k, m_k$ by (20)
- 10: $I^{(r)}(x_{\mathcal{K}})$ by (11), (13), (15)
- 11: **Repeat**
- 12: Update $r \leftarrow r+1$
- 13: $\mathbf{p}_k^{(r)}, \forall k$ by (21)
- 14: Redo step 7–10
- 15: **Until** $I^{(r)}(x_{\mathcal{K}}) - I^{(r-1)}(x_{\mathcal{K}}) \leq \epsilon$

where r is the iteration index.

Proof. Please refer to Appendix B. \square

At iteration $r+1$, the input distribution of node k is updated over $\{\{\mathbf{p}_q^{(r+1)}\}_{q=1}^{k-1}, \{\mathbf{p}_q^{(r)}\}_{q=k}^K\}$. The KKT input distribution design is summarized in Algorithm 1.

Remark 5. *The insufficiency of the KKT conditions for problem (18) implies that the proposed method may not converge to the global-optimal solution. However, simulation results show that the average performance gap is indistinguishable at a moderate K .*

B. Active Beamforming

For any given $\{\mathbf{p}_k\}_{k \in \mathcal{K}}$ and \mathbf{t} , problem (17) reduces to

$$\max_{\mathbf{w}} I(x_{\mathcal{K}}) \quad (22a)$$

$$\text{s.t.} \quad (17d), \quad (22b)$$

which is still non-convex due to the integration and entropy terms. Note the DMMAC $q(x_l|x_{m_{\mathcal{K}}})$ depends on the variance of accumulated receive energy $\sigma_{m_{\mathcal{K}}}^2$, which is a function of \mathbf{w} . Plugging (8) into (10), we have

$$q(x_l|x_{m_{\mathcal{K}}}) = \frac{\int_{t_{l-1}/\sigma_{m_{\mathcal{K}}}^2}^{t_l/\sigma_{m_{\mathcal{K}}}^2} z^{N-1} \exp(-z) dz}{(N-1)!} \quad (23)$$

$$= Q\left(N, \frac{t_{l-1}}{\sigma_{m_{\mathcal{K}}}^2}, \frac{t_l}{\sigma_{m_{\mathcal{K}}}^2}\right), \quad (24)$$

where $Q(N, b_1, b_2) \triangleq \int_{b_1}^{b_2} z^{N-1} \exp(-z) / (N-1)! dz$ is the regularized incomplete Gamma function. Its series expansion

is given by [60, Theorem 3]

$$Q\left(N, \frac{t_{l-1}}{\sigma_{m_K}^2}, \frac{t_l}{\sigma_{m_K}^2}\right) = \exp\left(-\frac{t_{l-1}}{\sigma_{m_K}^2}\right) \sum_{n=0}^{N-1} \frac{\left(\frac{t_{l-1}}{\sigma_{m_K}^2}\right)^n}{n!} \\ - \exp\left(-\frac{t_l}{\sigma_{m_K}^2}\right) \sum_{n=0}^{N-1} \frac{\left(\frac{t_l}{\sigma_{m_K}^2}\right)^n}{n!}, \quad (25)$$

whose gradient with respect to \mathbf{w}^* is

$$\nabla_{\mathbf{w}^*} Q\left(N, \frac{t_{l-1}}{\sigma_{m_K}^2}, \frac{t_l}{\sigma_{m_K}^2}\right) = \frac{\mathbf{h}(x_{m_K}) \mathbf{h}^H(x_{m_K}) \mathbf{w}}{(\sigma_{m_K}^2)^2} \\ \times \left(g_{m_K}(t_l) - g_{m_K}(t_{l-1})\right), \quad (26)$$

where

$$g_{m_K}(t_l) = t_l \exp\left(-\frac{t_l}{\sigma_{m_K}^2}\right) \left(-1 + \sum_{n=1}^{N-1} \frac{\left(n - \frac{t_l}{\sigma_{m_K}^2}\right) \left(\frac{t_l}{\sigma_{m_K}^2}\right)^{n-1}}{n!}\right). \quad (27)$$

On top of (25) and (26), we rewrite $I(x_K)$ and $\nabla_{\mathbf{w}^*} I(x_K)$ as (28) and (29) at the end of page 7, respectively. Problem (22) can thus be solved by the PGA method. At each iteration r , the unregulated active beamformer is updated by

$$\bar{\mathbf{w}}^{(r)} = \mathbf{w}^{(r-1)} + \gamma \nabla_{\mathbf{w}^*} I^{(r-1)}(x_K), \quad (30)$$

where γ is the step size (refinable by backtracking line search [61, Section 9.2]). Then, $\bar{\mathbf{w}}$ is projected onto the feasible domain (17d) to retrieve the active beamformer

$$\mathbf{w} = \frac{\sqrt{P} \bar{\mathbf{w}}}{\max(\sqrt{P}, \|\bar{\mathbf{w}}\|)}. \quad (31)$$

The PGA active beamforming design is summarized in Algorithm 2.

C. Decision Threshold

For any given $\{\mathbf{p}_k\}_{k \in \mathcal{K}}$ and \mathbf{w} , problem (17) reduces to

$$\max_{\mathbf{t}} I(x_K) \quad (32a)$$

$$\text{s.t.} \quad (17e), (17f), \quad (32b)$$

which is still non-convex since \mathbf{t} appears on the limits of integration (10). Instead of solving it directly, we constrain the feasible domain from continuous space \mathbb{R}_+^{L+1} to discrete candidates

Algorithm 2: Active Beamforming Optimization by PGA

Input: $Q, N, \mathbf{h}_D^H, \mathbf{H}_C, \boldsymbol{\alpha}, \mathcal{X}, P, \sigma_v^2, \rho, \{\mathbf{p}_k\}_{k \in \mathcal{K}}, \mathbf{t}, \alpha, \beta, \gamma, \epsilon$

Output: \mathbf{w}^*

- 1: Set $\mathbf{h}^H(x_{m_K}), \forall m_K$ by (4)
 - 2: $p(x_{m_K}), \forall m_K$ by (6)
 - 3: Initialize $r \leftarrow 0$
 - 4: $\mathbf{w}^{(0)}, \|\mathbf{w}^{(0)}\|^2 \leq P$
 - 5: Get $(\sigma_{m_K}^{(r)})^2, \forall m_K$ by (7)
 - 6: $Q^{(r)}(N, \frac{t_{l-1}}{\sigma_{m_K}^2}, \frac{t_l}{\sigma_{m_K}^2}), \forall m_K, l$ by (25)
 - 7: $I^{(r)}(x_K)$ by (28)
 - 8: $\nabla_{\mathbf{w}^*} Q^{(r)}(N, \frac{t_{l-1}}{\sigma_{m_K}^2}, \frac{t_l}{\sigma_{m_K}^2}), \forall m_K, l$ by (26)
 - 9: $\nabla_{\mathbf{w}^*} I^{(r)}(x_K)$ by (29)
 - 10: **Repeat**
 - 11: Update $r \leftarrow r + 1$
 - 12: $\gamma^{(r)} \leftarrow \gamma$
 - 13: $\bar{\mathbf{w}}^{(r)}$ by (30)
 - 14: $\mathbf{w}^{(r)}$ by (31)
 - 15: Redo step 5–7
 - 16: **While** $I^{(r)}(x_K) < I^{(r-1)}(x_K) + \alpha \gamma \|\nabla_{\mathbf{w}^*} I^{(r-1)}(x_K)\|^2$
 - 17: Set $\gamma^{(r)} \leftarrow \beta \gamma^{(r)}$
 - 18: Redo step 13–15
 - 19: **End While**
 - 20: Redo step 8, 9
 - 21: **Until** $\|\mathbf{w}^{(r)} - \mathbf{w}^{(r-1)}\| \leq \epsilon$
-

(i.e., fine-grained energy levels) \mathcal{T}^{L+1} . As shown in Fig. 6, grouping adjacent energy bins formulates decision regions.

Remark 6. The design of the energy detector does not affect the primary achievable rate, since the composite channel (4) can always be determined after backscatter decoding and re-encoding. This implies that any thresholding maximizing the total backscatter rate is optimal for problem (32).

Remark 7. In terms of total backscatter rate, the nodes can be viewed as an augmented source, and problem (32) becomes the rate-optimal quantizer design for DMTC.

$$I(x_K) = \sum_{m_K} p(x_{m_K}) \left(\rho \log\left(1 + \frac{|\mathbf{h}^H(x_{m_K}) \mathbf{w}|^2}{\sigma_v^2}\right) + (1-\rho) \sum_l Q\left(N, \frac{t_{l-1}}{\sigma_{m_K}^2}, \frac{t_l}{\sigma_{m_K}^2}\right) \log \frac{Q\left(N, \frac{t_{l-1}}{\sigma_{m_K}^2}, \frac{t_l}{\sigma_{m_K}^2}\right)}{\sum_{m'_K} p(x_{m'_K}) Q\left(N, \frac{t_{l-1}}{\sigma_{m'_K}^2}, \frac{t_l}{\sigma_{m'_K}^2}\right)} \right) \quad (28)$$

$$\nabla_{\mathbf{w}^*} I(x_K) = \sum_{m_K} p(x_{m_K}) \left(\rho \frac{\mathbf{h}(x_{m_K}) \mathbf{h}^H(x_{m_K}) \mathbf{w}}{\sigma_{m_K}^2} + (1-\rho) \sum_l \left(\log \frac{Q\left(N, \frac{t_{l-1}}{\sigma_{m_K}^2}, \frac{t_l}{\sigma_{m_K}^2}\right)}{\sum_{m'_K} p(x_{m'_K}) Q\left(N, \frac{t_{l-1}}{\sigma_{m'_K}^2}, \frac{t_l}{\sigma_{m'_K}^2}\right)} + 1 \right) \right. \\ \left. \times \nabla_{\mathbf{w}^*} Q\left(N, \frac{t_{l-1}}{\sigma_{m_K}^2}, \frac{t_l}{\sigma_{m_K}^2}\right) - \frac{Q\left(N, \frac{t_{l-1}}{\sigma_{m_K}^2}, \frac{t_l}{\sigma_{m_K}^2}\right) \sum_{m'_K} p(x_{m'_K}) \nabla_{\mathbf{w}^*} Q\left(N, \frac{t_{l-1}}{\sigma_{m'_K}^2}, \frac{t_l}{\sigma_{m'_K}^2}\right)}{\sum_{m'_K} p(x_{m'_K}) Q\left(N, \frac{t_{l-1}}{\sigma_{m'_K}^2}, \frac{t_l}{\sigma_{m'_K}^2}\right)} \right) \quad (29)$$

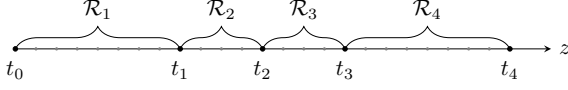


Fig. 6. The thresholds are chosen from fine-grained candidates instead of the continuous space. Each decision region consists of at least one bin.

Thanks to Remark 6 and 7, problem (32) can be recast as

$$\max_{\mathbf{t} \in \mathcal{T}^{L+1}} I_B(x_{\mathcal{K}}; \hat{x}_{\mathcal{K}}) \quad (33a)$$

$$\text{s.t.} \quad (17e), \quad (33b)$$

whose global optimal solution has been obtained in recent works. [62] started from the quadrangle inequality and proposed a Dynamic Programming (DP) method accelerated by the Shor-Moran-Aggarwal-Wilber-Klawe (SMAWK) algorithm with computational complexity $\mathcal{O}(L^2(\text{card}(\mathcal{T})-L))$. On the other hand, [63] started from the optimality condition for three neighbor thresholds and presented a traverse-then-bisect algorithm with complexity $\mathcal{O}(\text{card}(\mathcal{T})L\log(\text{card}(\mathcal{T})L))$. In Section IV, both schemes will be compared with the ML scheme [64]

$$t_l^{\text{ML}} = N \frac{\sigma_{l-1}^2 \sigma_l^2}{\sigma_{l-1}^2 - \sigma_l^2} \log \frac{\sigma_{l-1}^2}{\sigma_l^2}, \quad l \in \mathcal{L} \setminus \{L\}, \quad (34)$$

which is suboptimal for problem (32) unless all nodes are with equiprobable inputs.

IV. SIMULATION RESULTS

In this section, we provide numerical results to evaluate the proposed input distribution, active beamforming, and backscatter decision algorithms. We assume the AP-user distance is 10 m and at least one RISscatter nodes are randomly dropped in a disk centered at the user with radius r . The AP is with an average transmit power budget $P = 36\text{dBm}$ and all nodes employs M -QAM with $\alpha = 0.5$. For all channels involved, we consider a distance-dependent path loss model

$$L(d) = L_0 \left(\frac{d_0}{d} \right)^\gamma, \quad (35)$$

together with a Rician fading model

$$\mathbf{H} = \sqrt{\frac{\kappa}{1+\kappa}} \bar{\mathbf{H}} + \sqrt{\frac{1}{1+\kappa}} \tilde{\mathbf{H}}, \quad (36)$$

where d is the transmission distance, $L_0 = -30\text{dB}$ is the reference path loss at $d_0 = 1\text{m}$, κ is the Rician K-factor, $\bar{\mathbf{H}}$ is the deterministic line-of-sight component with unit-magnitude entries, and $\tilde{\mathbf{H}}$ is the Rayleigh fading component with standard independent and identically distributed (i.i.d.) CSCG entries. We choose $\gamma_D = 2.6$, $\gamma_F = 2.4$, $\gamma_B = 2$, and $\kappa_D = \kappa_F = \kappa_B = 5$ for direct, forward and backward links. The finite decision threshold domain \mathcal{T} is obtained by b -bit uniform discretization over the critical interval defined by the confidence bounds of edge hypotheses (i.e., lower bound of x_1 and upper bound of x_L) with confidence $1 - \varepsilon$. We set $b = 9$ and $\varepsilon = 10^{-3}$. All achievable rate regions are averaged over 10^3 channel realizations.

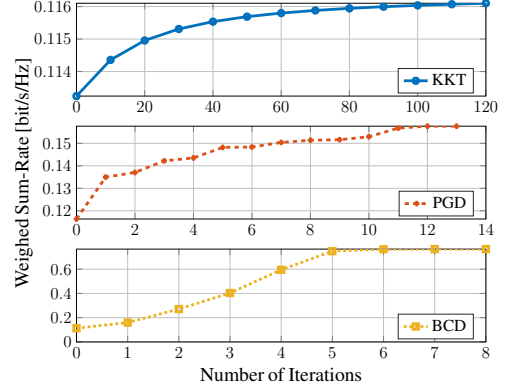


Fig. 7. Typical convergence curves at $\rho = 0$ for $Q = 4$, $K = 8$, $M = 2$, $N = 20$, $\sigma_v^2 = -40\text{dBm}$ and $r = 2\text{m}$.

A. Evaluation of Proposed Algorithms

1) *Initialization*: To characterize the achievable rate region, we progressively obtain all boundary points by successively increasing ρ and solving problem (17). For $\rho = 0$ where the backscatter link is prioritized, we initialize Algorithm 1 and 2 by uniform input distribution and Maximum Ratio Transmission (MRT) towards the sum cascaded channel $\sum_k \mathbf{h}_{C,k}^H$, respectively. At the following points, both algorithms are initialized by the solutions at the previous point.

2) *Convergence*: The BCD algorithm is convergent for problem (17) since the input distribution and active beamforming subproblems converge and the thresholding subproblem attains global optimality. In company with BCD, we also plotted the convergence results of KKT and PGA algorithms in Fig. 7 to show how much performance is gained by solving each subproblem. It is observed that Algorithm 1 and 2 take around 100 and 10 iterations to converge, respectively. Overall, the BCD algorithm requires at most 5 iterations to converge. As ρ increases (not presented here), the convergence of all three algorithms are much faster thanks to the progressive initialization.

B. Comparison of Scattering Applications

On top of the setup in Fig. 4, we consider RISscatter and the following benchmark applications:

- *Legacy*: Active transmission without scatterers.
- *BBC*: The primary symbol becomes deterministic $s[n] = 1$ and the receive signal becomes

$$y^{\text{BBC}}[n] = \left(\mathbf{h}_D^H + \sum_k \alpha_k \mathbf{h}_{C,k}^H x_k \right) \mathbf{w} + v[n]. \quad (37)$$

The total backscatter rate of coherent decoding approaches $K \log M$ when N is sufficiently large.

- *AmBC*: The user decodes both links independently and semi-coherently by treating the other as interference. The primary achievable rate is approximately¹²

$$I_P^{\text{AmBC}}(s; y) \approx \log \left(1 + \frac{|\mathbf{h}_D^H \mathbf{w}|^2}{\sum_k |\alpha_k \mathbf{h}_{C,k}^H \mathbf{w}|^2 + \sigma_v^2} \right), \quad (38)$$

¹²The scattered component is treated as interference with average power $\mathbb{E}\{\sum_k \alpha_k \mathbf{h}_{C,k}^H x_k \mathbf{w} s[n]\} = \sum_k |\alpha_k \mathbf{h}_{C,k}^H \mathbf{w}|^2$ [13].

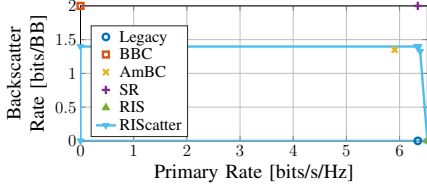


Fig. 8. Typical achievable rate region/points of scattering applications for $Q=1$, $K=1$, $M=4$, $N=10^3$, $\sigma_v^2=-40\text{dBm}$ and $r=2\text{m}$.

while the total backscatter rate follows (11) with uniform input distribution.

- *SR*: For a sufficiently large N , the average primary rate under semi-coherent detection asymptotically approaches (13) with uniform input distribution [13]. When $s[n]$ is successfully decoded and the direct interference $\mathbf{h}_D^H \mathbf{w} s[n]$ is perfectly cancelled, the intermediate signal is

$$\hat{y}^{\text{SR}}[n] = \sum_k \alpha_k \mathbf{h}_{C,k}^H x_k \mathbf{w} s[n] + v[n]. \quad (39)$$

The total backscatter rate of coherent decoding approaches $K \log M$ when N is sufficiently large.

- *RIS*: The reflection pattern is deterministic and the total backscatter rate is zero. The primary achievable rate is a special case of (13)

$$I_P^{\text{RIS}}(s; y | x_{\mathcal{K}}) = I_P(s; y | x_{m_{\mathcal{K}}^*}) = \log \left(1 + \frac{|\mathbf{h}^H(x_{m_{\mathcal{K}}^*}) \mathbf{w}|^2}{\sigma_v^2} \right), \quad (40)$$

where $m_{\mathcal{K}}^* = \arg \max_{m_{\mathcal{K}}} I_P^{\text{RIS}}(s; y | x_{m_{\mathcal{K}}})$.

Fig. 8 compares the typical achievable rate region/points of RIScatter and those strategies. *First*, we observe BBC and SR achieve the best backscatter performance thanks to coherent decoding. For SR, this comes with the cost of N re-encoding, precoding, subtraction together with a time-domain MRC per backscatter symbol. *Second*, the average primary rate slightly decreases/increases in the presence of a AmBC/RIS node and the benefit of SR is not obvious. This is because the cascaded channel is usually orders of magnitude weaker than the direct channel. Here, RIS ensures constructive superposition of direct and scattered components while SR only creates a quasi-static rich-scattering environment that marginally enhances the average primary rate. When N is moderate, the randomly scattered signals should be modelled as interference rather than multipath components and the SR point should move towards the AmBC point. *Third*, RIScatter enables a flexible primary-backscatter tradeoff with adaptive input distribution design. In terms of maximum primary achievable rate, RIScatter coincides with RIS and outperforms the others using deterministic reflection pattern. On the other hand, for a large N , the maximum backscatter achievable rate of RIScatter is lower than BBC and SR but higher than AmBC. This is because both RIScatter and AmBC employ semi-coherent energy detection, and the adaptive channel coding of RIScatter outperforms the equiprobable inputs of AmBC, especially at the low backscatter SNR in the double fading scenario. When multiple antenna is available at the AP, active beamforming can be optimized for

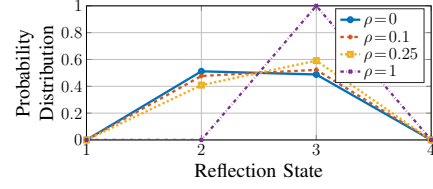


Fig. 9. Typical RIScatter reflection state distribution at different ρ for $Q=1$, $K=1$, $M=4$, $N=20$, $\sigma_v^2=-40\text{dBm}$ and $r=2\text{m}$.

RIScatter nodes and the backscatter rate gain over AmBC is more prominent.

C. Input Distribution under Different QoS

The objective is to demonstrate RIScatter nodes can leverage CSI- and QoS-adaptive input distribution design to balance backscatter modulation and passive beamforming. For one RIScatter node with $M=4$, we evaluate the KKT input distribution at different QoS and present the result in Fig. 9. At $\rho=0$ where the backscatter performance is prioritized, the optimal input distribution is 0 on two states and nearly uniform on the other two. This is inline with Shannon's observation that binary antipodal inputs is good enough for channel capacity at the low SNR [65]. Due to the weak scattered signal, the conditional energy PDF under different hypotheses can be closely spaced as in Fig. 5. The extreme states producing the lowest/highest energy are always assigned with non-zero probability, while the middles cannot provide enough energy difference and thus end up unused. At $\rho=1$ where the primary performance is prioritized, the optimal input distribution is 1 at the state that maximizes the primary SNR and 0 at the others. That is, the reflection pattern becomes deterministic and the RIScatter node boils down to a discrete RIS element. Increasing ρ from 0 to 1 provides a smooth transition from backscatter modulation to passive beamforming, suggesting RIScatter unifies BackCom and RIS from a probabilistic perspective.

D. Rate Region by Different Schemes

1) *Input Distribution*: We compare these input distribution designs for problem (18):

- *Cooperation*: Joint encoding using a joint probability array $p(x_{m_{\mathcal{K}}})$ with M^K entries by Algorithm 1;
- *Exhaustion*: Exhaustive search over the M -dimensional probability simplex with resolution $\Delta p=10^{-2}$;
- *KKT*: The KKT solution by Algorithm 1;
- *Equiprobable*: Uniform input distribution.

We also consider these independent distribution recovery methods from the joint probability array:

- *Marginalization*: Marginal probability distributions;
- *Decomposition*: Normalized rank-1 Canonical Polyadic (CP) decomposed tensors by `Tensor Toolbox` [66];
- *Randomization*: Gaussian randomization with the guidance of correlation matrix [67].

Fig. 10(a) shows their average achievable rate regions. It is observed that Cooperation achieves the outer bound of

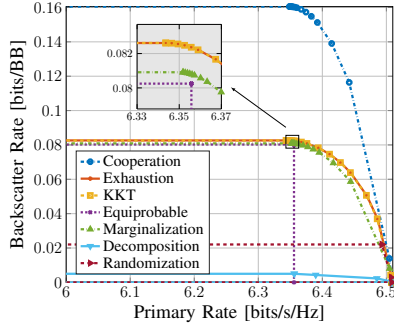
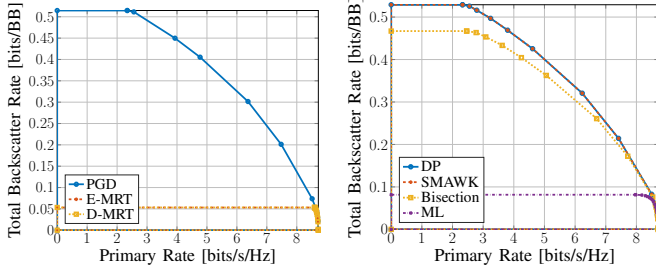
(a) Input Distribution, $Q = 1$ (b) Active Beamforming, $Q = 4$ (c) Decision Threshold, $Q = 4$

Fig. 10. Average primary-total-backscatter rate regions by different input distribution, active beamforming, and decision threshold schemes for $K=2$, $M=4$, $N=20$, $\sigma_v^2=-40\text{dBm}$ and $r=2\text{m}$.

all schemes, but its backscatter rate gain comes at the cost of implementation and computation complexity. Besides, the average rate performance of Exhaustion and KKT completely coincide with each other when $K=2$. This confirms Remark 5 that the KKT input distribution can be good enough when K is not very large. Equiprobable experiences minor backscatter and major primary rate losses without exploiting CSI and QoS. Those gaps should be larger when M and/or K increase. For the recovery methods, Marginalization provides a close performance to KKT, but Randomization and Decomposition fail our expectations for most channel realizations. Those observations emphasize the importance of adaptive RIScatter encoding and demonstrate the advantage of the proposed KKT input distribution design.

2) *Active Beamforming*: We consider three typical active beamforming schemes for problem (22):

- *PGA*: Iterative PGA optimization by Algorithm 2;
- *E-MRT*: MRT towards the ergodic composite channel $\sum_{m_K} p(x_{m_K}) \mathbf{h}^H(x_{m_K})$;
- *D-MRT*: MRT towards the direct channel \mathbf{h}_D^H .

Fig. 10(b) presents the average achievable rate regions for those schemes. In the low- ρ regime, the proposed PGA beamformer significantly outperforms both MRT schemes in terms of total backscatter rate. This is because the semi-coherent backscatter decoding relies on the *relative difference* of receive energy under different backscatter symbol tuples. Such an energy diversity is enhanced by PGA, which effectively exploits backscatter constellation and input distribution knowledge rather than simply maximizing the direct/ergodic channel strength. As ρ increases, the primary SNR outweighs the backscatter energy difference in (28), and PGA beamformer

approaches both MRT schemes. At $\rho=1$, both PGA and E-MRT boil down to MRT towards the composite channel. The difference between E-MRT and D-MRT is insignificant when RIScatter nodes are dispersed. Those observations prove the proposed PGA active beamforming design can exploit the CSI, QoS, and backscatter constellation to enlarge the achievable rate region.

3) *Decision Threshold*: We evaluate the following decision threshold strategies for problem (33):

- *DP*: Benchmark DP method for sequential quantizer [62];
- *SMAWK*: DP accelerated by the SMAWK algorithm [62];
- *Bisection*: The traverse-then-bisect algorithm [63];
- *ML*: Maximum likelihood detector (34) [64].

Fig. 10(c) reveals the average achievable rate region for those strategies. The distribution-aware schemes DP, SMAWK and Bisection ensure higher total backscatter rate than ML. This is because the total backscatter rate (11) is a function of both input distribution and decision regions, and the rate-optimal threshold design heavily depends on input distribution. For example, the backscatter symbol tuples with zero input probability should be assigned with empty decision regions, in order to increase the success detection rates of other hypotheses. It highlights the importance of joint input distribution and decision threshold design in rate maximization problems.

E. Rate Region under Different Configurations

In this study, we choose $Q = 4$, $K = 8$, $M = 2$, $N = 20$, $\sigma_v^2 = -40\text{dBm}$ and $r = 2\text{m}$ as a reference.

1) *Number of Nodes*: Fig. 11(a) reveals how the number RIScatter nodes K influence the primary-backscatter tradeoff. Interestingly, we observe that increasing K has a larger benefit on the total backscatter rate than primary. This is because each RIScatter node not only affects the primary SNR but also influences the relative energy difference that other nodes can make. To maximize the total backscatter rate, some nodes closer to the user may need to sacrifice their own rate and use the state that *minimizes* the composite channel strength, in order to increase the backscatter rate of other nodes. This accounts for the significant primary rate decrease in the low- ρ regime. On the other hand, when the primary link is prioritized, the RIScatter nodes boil down to RIS elements and enjoy a conventional passive array gain K^2 .

2) *Number of States*: Fig. 11(b) shows the relationship between available reflection states (i.e., QAM order) M and achievable rate regions when $K=1$. We notice that increasing the reflection states has a marginal effect on the primary rate but significantly improves the backscatter rate. This is because the maximum amplitude normalized-QAM (2) involves more weak reflection points as M increases. It greatly enhances the receive energy difference but cannot provide enough phase shift resolution with strong reflection.

3) *Number of Transmit Antennas*: Fig. 11(c) illustrates the impact of transmit antennas Q on the average performance. As Q increases, more scattered paths are available to PGA and the channel diversity can be further exploited to enhance the primary SNR and backscatter energy difference. It emphasizes the importance of multi-antenna RIScatter systems and demonstrate the effectiveness of the proposed PGA design.

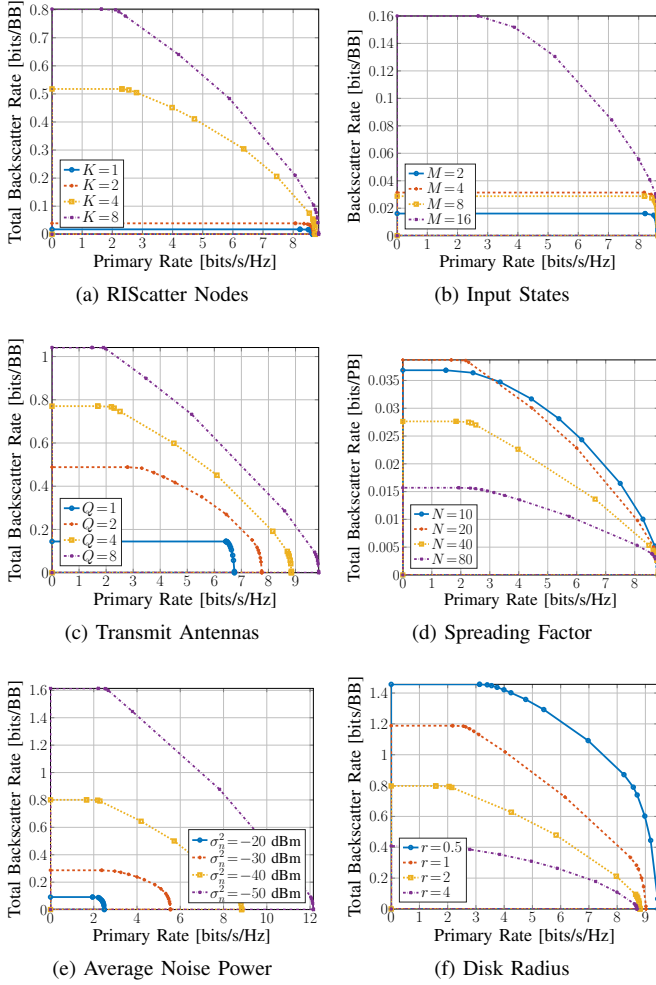


Fig. 11. Average primary-total-backscatter rate regions for different system configurations.

4) *Spreading factor*: Fig. 11(d) shows how the spreading factor N affects the achievable rate region.¹³ Using a very large N can severely constrain the backscatter throughput, since the gain in energy certainty (by law of large numbers) cannot withstand the loss in gross rate. As $N \rightarrow \infty$, RISscatter nodes boil down to static RIS elements and the total backscatter rate approaches 0. On the other hand, when N is too small, energy detection is error-prone as the DMMAC (10) is unreliable. It explains the observation that $N = 10$ provides lower backscatter throughput than $N = 20$. Therefore, we conclude the spreading factor N should be carefully designed over multiple factors (e.g., data rate requirements, load switching speed at the nodes, and signal processing capability at the user).

5) *Average Noise Power*: Fig. 11(e) depicts the impact of average noise power σ_v^2 on average rate regions. It shows the proposed practical semi-coherent backscatter energy detection is suitable for a wide range of noise levels. When σ_v^2 relatively high, one can choose a larger N to maintain the backscatter SNR for better energy detection performance.

6) *Coverage Disk Radius*: Fig. 11(f) shows the relationship

between disk radius r and achievable rate region. We observe both primary and backscatter performance are enhanced when nodes are located closer to the user. This is because the double fading effect is less severe for near-far setups. In a multi-user RISscatter network with dispersed nodes, each node may be assigned to the nearest user to guarantee uniformly good performance for both links.

V. CONCLUSION

This paper introduced RISscatter as a novel scatter protocol that bridges backscatter modulation and passive beamforming. Starting from scattering principles, we showed how RISscatter nodes generalize information nodes of BackCom and reflect elements of RIS, how they can be built over existing passive scatter devices, and how they simultaneously encode self information and assist legacy transmission. We also proposed a practical SIC-free receiver that exploits the properties of active-passive coexisting networks to benefit both subsystems. The achievable primary-total-backscatter rate region was then studied for a single-user multi-node RISscatter network, where the input distribution, active beamforming, and decision thresholds are iteratively updated. Numerical results validated the proposed algorithms and emphasized the importance of adaptive input distribution and cooperative receiver design.

One possible future direction is to consider backscatter detection over the received signal domain rather than energy domain, where multi-antenna [68] and learning-based approaches can be promising. Another interesting question is how to design RISscatter node and receiver in a multi-user system to fully exploit the dynamic passive beamforming that naturally originates from backscatter modulation.

APPENDIX

A. Proof of Proposition 1

Denote the Lagrange multipliers associated with (17b) and (17c) as $\{\nu_k\}_{k \in \mathcal{K}}$ and $\{\lambda_{m_k}\}_{k \in \mathcal{K}, m_k \in \mathcal{M}}$, respectively. The Lagrangian function of problem (18) is

$$I(x_{\mathcal{K}}) + \sum_k \nu_k \left(\sum_{m_k} p(x_{m_k}) - 1 \right) + \sum_k \sum_{m_k} \lambda_{m_k} p(x_{m_k}) \quad (41)$$

and the KKT conditions are, $\forall k, m_k$,

$$I_k^*(x_{m_k}) - (1 - \rho) + \nu_k^* + \lambda_{m_k}^* = 0, \quad (42a)$$

$$\lambda_{m_k}^* = 0, \quad \text{if } p^*(x_{m_k}) > 0, \quad (42b)$$

$$\lambda_{m_k}^* \geq 0, \quad \text{if } p^*(x_{m_k}) = 0. \quad (42c)$$

Plugging (42b) and (42c) into (42a) yields

$$I_k^*(x_{m_k}) = 1 - \rho - \nu_k^*, \quad \text{if } p^*(x_{m_k}) > 0, \quad (43a)$$

$$I_k^*(x_{m_k}) \leq 1 - \rho - \nu_k^*, \quad \text{if } p^*(x_{m_k}) = 0, \quad (43b)$$

such that

$$\sum_{m_k} p^*(x_{m_k}) I_k^*(x_{m_k}) = 1 - \rho - \nu_k^*. \quad (44)$$

On the other hand, by definition (20) we have

$$\sum_{m_k} p^*(x_{m_k}) I_k^*(x_{m_k}) = I^*(x_{\mathcal{K}}), \quad (45)$$

where the right-hand side is irrelevant to k . (43), (44), and (45) together complete the proof.

¹³Please notice in Fig. 11(d) the unit of total backscatter rate is bits per primary block to indicate throughput.

B. Proof of Proposition 2

We first prove sequence (21) is non-decreasing in weighted sum mutual information. Let $p(x_{m_K}) = \prod_{q \in K} p(x_{m_q})$ and $p'(x_{m_K}) = p'(x_{m_k}) \prod_{q \in K \setminus \{k\}} p(x_{m_q})$ be two distributions potentially different at x_{m_k} , and $J(p(x_{m_K}), p'(x_{m_K}))$ be a joint function defined in (46) at the end of page 12. It is straightforward to verify $J(p(x_{m_K}), p(x_{m_K})) = I(x_K)$ and $J(p(x_{m_K}), p'(x_{m_K}))$ is a concave function for a given $p'(x_{m_K})$. Setting $\nabla_{p(x_{m_K})} J(p(x_{m_K}), p'(x_{m_K})) = 0$ yields

$$S'_k(x_{m_k}) - S'_k(x_{i_k}) + (1-\rho) \log \frac{p(x_{i_k})}{p^*(x_{m_k})} = 0, \quad (47)$$

where $i_k \neq m_k$ is the reference state and

$$S'_k(x_{m_k}) \triangleq I'_k(x_{m_k}) + (1-\rho) \sum_{m_K \setminus \{k\}} p(x_{m_K \setminus \{k\}}) \times \sum_{m'_K} q(\hat{x}_{m'_K} | x_{m_K}) \log p'(x_{m_K}). \quad (48)$$

Evidently, $\forall m_k \neq i_k$, (47) boils down to

$$p^*(x_{m_k}) = \frac{p'(x_{m_k}) \exp\left(\frac{\rho}{1-\rho} I'_k(x_{m_k})\right)}{\sum_{m'_K} p'(x_{m'_K}) \exp\left(\frac{\rho}{1-\rho} I'_k(x_{m'_K})\right)}. \quad (49)$$

Since $p(x_{i_k}) = 1 - \sum_{m_k \neq i_k} p^*(x_{m_k})$ has exactly the same form as (49), the choice of reference does not matter and (49) is optimal $\forall m_k \in \mathcal{M}$. That is, for a fixed $p'(x_{m_K})$, (49) ensures

$$J(p(x_{m_K}), p'(x_{m_K})) \geq I'(x_K). \quad (50)$$

On the other hand, we notice

$$\begin{aligned} I(x_K) - J(p(x_{m_K}), p'(x_{m_K})) \\ = (1-\rho) \sum_{m_k} \frac{p'(x_{m_k}) f'_k(x_{m_k})}{\sum_{m'_K} p'(x_{m'_K}) f'_k(x_{m'_K})} \sum_{m''_K} q(\hat{x}_{m''_K} | x_{m_k}) \\ \times \log \frac{\sum_{m'_K} p'(x_{m'_K}) q(\hat{x}_{m'_K} | x_{m'_K}) f'_k(x_{m_k})}{\sum_{m'_K} p'(x_{m'_K}) q(\hat{x}_{m'_K} | x_{m'_K}) f'_k(x_{m'_K})} \end{aligned} \quad (51a)$$

$$\begin{aligned} \geq (1-\rho) \sum_{m_k} \frac{p'(x_{m_k}) f'_k(x_{m_k})}{\sum_{m'_K} p'(x_{m'_K}) f'_k(x_{m'_K})} \sum_{m''_K} q(\hat{x}_{m''_K} | x_{m_k}) \\ \times \left(1 - \frac{\sum_{m'_K} p'(x_{m'_K}) q(\hat{x}_{m'_K} | x_{m'_K}) f'_k(x_{m'_K})}{\sum_{m'_K} p'(x_{m'_K}) q(\hat{x}_{m'_K} | x_{m'_K}) f'_k(x_{m_k})}\right) \end{aligned} \quad (51b)$$

$$\begin{aligned} = (1-\rho) \left(1 - \sum_{m_k} \frac{p'(x_{m_k}) f'_k(x_{m_k})}{\sum_{m'_K} p'(x_{m'_K}) f'_k(x_{m'_K})} \sum_{m''_K} q(\hat{x}_{m''_K} | x_{m_k}) \right. \\ \left. \times \frac{\sum_{m'_K} p'(x_{m'_K}) q(\hat{x}_{m'_K} | x_{m'_K}) f'_k(x_{m'_K})}{\sum_{m'_K} p'(x_{m'_K}) q(\hat{x}_{m'_K} | x_{m'_K}) f'_k(x_{m_k})}\right) \end{aligned} \quad (51c)$$

$$J(p(x_{m_K}), p'(x_{m_K})) \triangleq \sum_{m_K} p(x_{m_K}) \left(\rho \log \left(1 + \frac{|\mathbf{h}^H(x_{m_K}) \mathbf{w}|^2}{\sigma_v^2}\right) + (1-\rho) \sum_{m'_K} q(\hat{x}_{m'_K} | x_{m_K}) \log \frac{q(\hat{x}_{m'_K} | x_{m_K}) p'(x_{m_K})}{p'(\hat{x}_{m'_K}) p(x_{m_K})} \right). \quad (46)$$

$$\begin{aligned} \times \frac{\sum_{m'_K} p'(x_{m'_K}) q(\hat{x}_{m'_K} | x_{m'_K}) f'_k(x_{m'_K})}{\sum_{m'_K} p'(x_{m'_K}) q(\hat{x}_{m'_K} | x_{m'_K})} \Big) \\ = (1-\rho) \left(1 - \frac{\sum_{m'_K} p'(x_{m'_K}) f'_k(x_{m'_K}) \sum_{m''_K} q(\hat{x}_{m''_K} | x_{m'_K})}{\sum_{m'_K} p'(x_{m'_K}) f'_k(x_{m'_K})}\right) \\ = 0, \end{aligned} \quad (51d) \quad (51e)$$

where $f'_k(x_{m_k}) \triangleq \exp\left(\frac{\rho}{1-\rho} I'_k(x_{m_k})\right)$ and the equality holds if and only if $p(x_{m_K})$ and $p'(x_{m_K})$ equals (i.e., (49) converges). (50) and (51) together imply $I(x_K) \geq I'(x_K)$. Since mutual information is bounded above, we conclude the sequence (21) is non-decreasing and convergent.

Next, we prove any converging point of sequence (21), denoted as $p^*(x_{m_K})$, fulfills KKT conditions (19). Let

$$D^{(r)}(x_{m_k}) \triangleq \frac{p^{(r+1)}(x_{m_k})}{p^{(r)}(x_{m_k})} = \frac{f_k^{(r)}(x_{m_k})}{\sum_{m'_K} p^{(r)}(x_{m'_K}) f_k^{(r)}(x_{m'_K})}. \quad (52)$$

As sequence (21) is convergent, any state with $p^*(x_{m_k}) > 0$ need to satisfy $D^*(x_{m_k}) \triangleq \lim_{r \rightarrow \infty} D^{(r)}(x_{m_k}) = 1$, namely

$$I_k^*(x_{m_k}) = \frac{1-\rho}{\rho} \log \sum_{m'_K} p^*(x_{m'_K}) \exp\left(\frac{\rho}{1-\rho} I_k^*(x_{m'_K})\right), \quad (53)$$

The right-hand side is a constant for node k and implies (43a). That is, any converging point with nonzero probability must satisfy (19a). On the other hand, we assume $p^*(x_{m_k}) = 0$ does not satisfy (19b), namely

$$I_k^*(x_{m_k}) > I^*(x_K) = \sum_{m'_K} p^*(x_{m'_K}) I_k^*(x_{m'_K}), \quad (54)$$

Since the exponential function is monotonically increasing, (54) implies $f_k^*(x_{m_k}) > \sum_{m'_K} p^*(x_{m'_K}) f_k^*(x_{m'_K})$ and $D^*(x_{m_k}) > 1$. It contradicts with

$$p^{(r)}(x_{m_k}) = p^{(0)}(x_{m_k}) \prod_{n=1}^r D^{(n)}(x_{m_k}), \quad (55)$$

since the left-hand side is zero while all terms on the right-hand side are strictly positive. The proof is completed.

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REFERENCES

- [1] C. Boyer and S. Roy, "Backscatter communication and RFID: Coding, energy, and MIMO analysis," *IEEE Transactions on Communications*, vol. 62, pp. 770–785, Mar 2014.
- [2] D. Dobkin, *The RF in RFID: Passive UHF RFID in Practice*. Newnes, Nov 2012.
- [3] J. Landt, "The history of RFID," *IEEE Potentials*, vol. 24, pp. 8–11, Oct 2005.

- [4] G. Vannucci, A. Bletsas, and D. Leigh, "A software-defined radio system for backscatter sensor networks," *IEEE Transactions on Wireless Communications*, vol. 7, pp. 2170–2179, Jun 2008.
- [5] S. D. Assimonis, S. N. Daskalakis, and A. Bletsas, "Sensitive and efficient RF harvesting supply for batteryless backscatter sensor networks," *IEEE Transactions on Microwave Theory and Techniques*, vol. 64, pp. 1327–1338, Apr 2016.
- [6] V. Liu, A. Parks, V. Talla, S. Gollakota, D. Wetherall, and J. R. Smith, "Ambient backscatter: Wireless communication out of thin air," *ACM SIGCOMM Computer Communication Review*, vol. 43, pp. 39–50, Sep 2013.
- [7] G. Yang, Q. Zhang, and Y.-C. Liang, "Cooperative ambient backscatter communications for green internet-of-things," *IEEE Internet of Things Journal*, vol. 5, pp. 1116–1130, Apr 2018.
- [8] Y.-C. Liang, Q. Zhang, E. G. Larsson, and G. Y. Li, "Symbiotic radio: Cognitive backscattering communications for future wireless networks," *IEEE Transactions on Cognitive Communications and Networking*, vol. 6, pp. 1242–1255, Dec 2020.
- [9] Q. Wu, S. Zhang, B. Zheng, C. You, and R. Zhang, "Intelligent reflecting surface-aided wireless communications: A tutorial," *IEEE Transactions on Communications*, vol. 69, pp. 3313–3351, May 2021.
- [10] H. Guo, Y.-C. Liang, R. Long, and Q. Zhang, "Cooperative ambient backscatter system: A symbiotic radio paradigm for passive IoT," *IEEE Wireless Communications Letters*, vol. 8, pp. 1191–1194, Aug 2019.
- [11] H. Ding, D. B. da Costa, and J. Ge, "Outage analysis for cooperative ambient backscatter systems," *IEEE Wireless Communications Letters*, vol. 9, pp. 601–605, May 2020.
- [12] R. Torres, R. Correia, N. Carvalho, S. N. Daskalakis, G. Goussetis, Y. Ding, A. Georgiadis, A. Eid, J. Hester, and M. M. Tentzeris, "Backscatter communications," *IEEE Journal of Microwaves*, vol. 1, pp. 864–878, Oct 2021.
- [13] R. Long, Y.-C. Liang, H. Guo, G. Yang, and R. Zhang, "Symbiotic radio: A new communication paradigm for passive internet of things," *IEEE Internet of Things Journal*, vol. 7, pp. 1350–1363, Feb 2020.
- [14] S. Zhou, W. Xu, K. Wang, C. Pan, M.-S. Alouini, and A. Nallanathan, "Ergodic rate analysis of cooperative ambient backscatter communication," *IEEE Wireless Communications Letters*, vol. 8, pp. 1679–1682, Dec 2019.
- [15] T. Wu, M. Jiang, Q. Zhang, Q. Li, and J. Qin, "Beamforming design in multiple-input-multiple-output symbiotic radio backscatter systems," *IEEE Communications Letters*, vol. 25, pp. 1949–1953, Jun 2021.
- [16] J. Xu, Z. Dai, and Y. Zeng, "Enabling full mutualism for symbiotic radio with massive backscatter devices," *arXiv:2106.05789*, Jun 2021.
- [17] Z. Yang and Y. Zhang, "Optimal SWIPT in RIS-aided MIMO networks," *IEEE Access*, vol. 9, pp. 112 552–112 560, 2021.
- [18] S. Han, Y.-C. Liang, and G. Sun, "The design and optimization of random code assisted multi-BD symbiotic radio system," *IEEE Transactions on Wireless Communications*, vol. 20, pp. 5159–5170, Aug 2021.
- [19] Q. Zhang, Y.-C. Liang, H.-C. Yang, and H. V. Poor, "Mutualistic mechanism in symbiotic radios: When can the primary and secondary transmissions be mutually beneficial?" *IEEE Transactions on Wireless Communications*, vol. 1276, pp. 1–1, 2022.
- [20] Q. Wu and R. Zhang, "Intelligent reflecting surface enhanced wireless network: Joint active and passive beamforming design," vol. 18. IEEE, Dec 2018, pp. 1–6.
- [21] S. Zhang and R. Zhang, "Capacity characterization for intelligent reflecting surface aided MIMO communication," *IEEE Journal on Selected Areas in Communications*, vol. 38, pp. 1823–1838, Aug 2020.
- [22] S. Lin, B. Zheng, F. Chen, and R. Zhang, "Intelligent reflecting surface-aided spectrum sensing for cognitive radio," *IEEE Wireless Communications Letters*, vol. 11, pp. 928–932, May 2022.
- [23] Y. Liu, Y. Zhang, X. Zhao, S. Geng, P. Qin, and Z. Zhou, "Dynamic-controlled RIS assisted multi-user MISO downlink system: Joint beamforming design," *IEEE Transactions on Green Communications and Networking*, vol. 6, pp. 1069–1081, Jun 2022.
- [24] Z. Feng, B. Clerckx, and Y. Zhao, "Waveform and beamforming design for intelligent reflecting surface aided wireless power transfer: Single-user and multi-user solutions," *IEEE Transactions on Wireless Communications*, 2022.
- [25] Y. Zhao, B. Clerckx, and Z. Feng, "IRS-aided SWIPT: Joint waveform, active and passive beamforming design under nonlinear harvester model," *IEEE Transactions on Communications*, vol. 70, pp. 1345–1359, 2022.
- [26] Y. Yang, S. Zhang, and R. Zhang, "IRS-enhanced OFDMA: Joint resource allocation and passive beamforming optimization," *IEEE Wireless Communications Letters*, vol. 9, pp. 760–764, Jun 2020.
- [27] Q. Wu, X. Zhou, and R. Schober, "IRS-assisted wireless powered NOMA: Do we really need different phase shifts in DL and UL?" *IEEE Wireless Communications Letters*, vol. 10, pp. 1493–1497, Jul 2021.
- [28] Q. Wu, X. Zhou, W. Chen, J. Li, and X. Zhang, "IRS-aided WPCNs: A new optimization framework for dynamic IRS beamforming," *IEEE Transactions on Wireless Communications*, pp. 1–1, Dec 2021.
- [29] M. Hua and Q. Wu, "Joint dynamic passive beamforming and resource allocation for IRS-aided full-duplex WPCN," *IEEE Transactions on Wireless Communications*, pp. 1–1, Dec 2021.
- [30] W. Tang, J. Y. Dai, M. Chen, X. Li, Q. Cheng, S. Jin, K.-K. Wong, and T. J. Cui, "Programmable metasurface-based RF chain-free 8PSK wireless transmitter," *Electronics Letters*, vol. 55, pp. 417–420, Apr 2019.
- [31] J. Y. Dai, W. Tang, L. X. Yang, X. Li, M. Z. Chen, J. C. Ke, Q. Cheng, S. Jin, and T. J. Cui, "Realization of multi-modulation schemes for wireless communication by time-domain digital coding metasurface," *IEEE Transactions on Antennas and Propagation*, vol. 68, pp. 1618–1627, Mar 2020.
- [32] R. Karasik, O. Simeone, M. D. Renzo, and S. S. Shitz, "Beyond max-SNR: Joint encoding for reconfigurable intelligent surfaces," vol. 2020-June. IEEE, Jun 2020, pp. 2965–2970.
- [33] R. Liu, H. Li, M. Li, and Q. Liu, "Symbol-level precoding design for intelligent reflecting surface assisted multi-user MIMO systems," IEEE, Oct 2019, pp. 1–6.
- [34] A. Bereyhi, V. Jamali, R. R. Muller, A. M. Tulino, G. Fischer, and R. Schober, "A single-RF architecture for multiuser massive MIMO via reflecting surfaces," IEEE, May 2020, pp. 8688–8692.
- [35] X. Xu, Y.-C. Liang, G. Yang, and L. Zhao, "Reconfigurable intelligent surface empowered symbiotic radio over broadcasting signals," vol. 2020-Janua. IEEE, Dec 2020, pp. 1–6.
- [36] Q. Zhang, Y.-C. Liang, and H. V. Poor, "Reconfigurable intelligent surface assisted MIMO symbiotic radio networks," *IEEE Transactions on Communications*, vol. 69, pp. 4832–4846, Jul 2021.
- [37] J. Hu, Y. C. Liang, and Y. Pei, "Reconfigurable intelligent surface enhanced multi-user MISO symbiotic radio system," *IEEE Transactions on Communications*, vol. 69, pp. 2359–2371, Apr 2021.
- [38] M. Hua, Q. Wu, L. Yang, R. Schober, and H. V. Poor, "A novel wireless communication paradigm for intelligent reflecting surface based symbiotic radio systems," *IEEE Transactions on Signal Processing*, vol. 70, pp. 550–565, Apr 2022.
- [39] E. Basar, "Reconfigurable intelligent surface-based index modulation: A new beyond MIMO paradigm for 6G," *IEEE Transactions on Communications*, vol. 68, pp. 3187–3196, May 2020.
- [40] T. Ma, Y. Xiao, X. Lei, P. Yang, X. Lei, and O. A. Dobre, "Large intelligent surface assisted wireless communications with spatial modulation and antenna selection," *IEEE Journal on Selected Areas in Communications*, vol. 38, pp. 2562–2574, Nov 2020.
- [41] J. Yuan, M. Wen, Q. Li, E. Basar, G. C. Alexandropoulos, and G. Chen, "Receive quadrature reflecting modulation for RIS-empowered wireless communications," *IEEE Transactions on Vehicular Technology*, vol. 70, pp. 5121–5125, May 2021.
- [42] S. Hu, C. Liu, Z. Wei, Y. Cai, D. W. K. Ng, and J. Yuan, "Beamforming design for intelligent reflecting surface-enhanced symbiotic radio systems," *arxiv:2110.10316*, Oct 2021.
- [43] Y. C. Liang, Q. Zhang, J. Wang, R. Long, H. Zhou, and G. Yang, "Backscatter communication assisted by reconfigurable intelligent surfaces," *Proceedings of the IEEE*, 2022.
- [44] S. J. Thomas and M. S. Reynolds, "A 96 mbit/sec, 15.5 pj/bit 16-qam modulator for uhf backscatter communication," IEEE, 4 2012, pp. 185–190.
- [45] N. V. Huynh, D. T. Hoang, X. Lu, D. Niyato, P. Wang, and D. I. Kim, "Ambient backscatter communications: A contemporary survey," *IEEE Communications Surveys & Tutorials*, vol. 20, pp. 2889–2922, 2018.
- [46] S. J. Thomas, E. Wheeler, J. Teizer, and M. S. Reynolds, "Quadrature amplitude modulated backscatter in passive and semipassive UHF RFID systems," *IEEE Transactions on Microwave Theory and Techniques*, vol. 60, pp. 1175–1182, Apr 2012.
- [47] J. Kim and B. Clerckx, "Wireless information and power transfer for IoT: Pulse position modulation, integrated receiver, and experimental validation," *IEEE Internet of Things Journal*, vol. 9, pp. 12 378–12 394, Jul 2022.
- [48] X. He, W. Jiang, M. Cheng, X. Zhou, P. Yang, and B. Kurkoski, "GuardRider: Reliable WiFi backscatter using reed-solomon codes with QoS guarantee," IEEE, Jun 2020, pp. 1–10.
- [49] Y. Huang, A. Alieldin, and C. Song, "Equivalent circuits and analysis of a generalized antenna system," *IEEE Antennas and Propagation Magazine*, vol. 63, pp. 53–62, Apr 2021.
- [50] D. Bharadia, K. R. Joshi, M. Kotaru, and S. Katti, "BackFi: High throughput WiFi backscatter," vol. 45. ACM, Aug 2015, pp. 283–296.
- [51] G. Yang, C. K. Ho, and Y. L. Guan, "Multi-antenna wireless energy transfer for backscatter communication systems," *IEEE Journal on Selected Areas in Communications*, vol. 33, pp. 2974–2987, Dec 2015.

- [52] H. Guo, Q. Zhang, S. Xiao, and Y.-C. Liang, "Exploiting multiple antennas for cognitive ambient backscatter communication," *IEEE Internet of Things Journal*, vol. 6, pp. 765–775, Feb 2019.
- [53] M. Jin, Y. He, C. Jiang, and Y. Liu, "Parallel backscatter: Channel estimation and beyond," *IEEE/ACM Transactions on Networking*, vol. 29, pp. 1128–1140, Jun 2021.
- [54] B. Zheng and R. Zhang, "Intelligent reflecting surface-enhanced OFDM: Channel estimation and reflection optimization," *IEEE Wireless Communications Letters*, vol. 9, pp. 518–522, Apr 2020.
- [55] C. You, B. Zheng, and R. Zhang, "Intelligent reflecting surface with discrete phase shifts: Channel estimation and passive beamforming," *IEEE*, Jun 2020, pp. 1–6.
- [56] W. Wu, X. Wang, A. Hawbani, L. Yuan, and W. Gong, "A survey on ambient backscatter communications: Principles, systems, applications, and challenges," 10 2022.
- [57] T. Nguyen, Y.-J. Chu, and T. Nguyen, "On the capacities of discrete memoryless thresholding channels," vol. 2018-June. *IEEE*, Jun 2018, pp. 1–5.
- [58] T. Nguyen and T. Nguyen, "Optimal quantizer structure for maximizing mutual information under constraints," *IEEE Transactions on Communications*, vol. 69, pp. 7406–7413, Nov 2021.
- [59] M. Rezaeian and A. Grant, "Computation of total capacity for discrete memoryless multiple-access channels," *IEEE Transactions on Information Theory*, vol. 50, pp. 2779–2784, Nov 2004.
- [60] G. J. O. Jameson, "The incomplete gamma functions," *The Mathematical Gazette*, vol. 100, pp. 298–306, Jul 2016.
- [61] S. Boyd and L. Vandenberghe, *Convex Optimization*. Cambridge University Press, Mar 2004.
- [62] X. He, K. Cai, W. Song, and Z. Mei, "Dynamic programming for sequential deterministic quantization of discrete memoryless channels," *IEEE Transactions on Communications*, vol. 69, pp. 3638–3651, Jun 2021.
- [63] T. Nguyen and T. Nguyen, "On thresholding quantizer design for mutual information maximization: Optimal structures and algorithms," vol. 2020-May. *IEEE*, May 2020, pp. 1–5.
- [64] J. Qian, A. N. Parks, J. R. Smith, F. Gao, and S. Jin, "IoT communications with M-PSK modulated ambient backscatter: Algorithm, analysis, and implementation," *IEEE Internet of Things Journal*, vol. 6, pp. 844–855, Feb 2019.
- [65] C. E. Shannon, "A mathematical theory of communication," *Bell System Technical Journal*, vol. 27, pp. 379–423, Jul 1948.
- [66] B. W. Bader and T. G. Kolda, "Tensor toolbox for MATLAB," <https://www.tensortoolbox.org/>, Sep 2022.
- [67] E. Calvo, D. P. Palomar, J. R. Fonollosa, and J. Vidal, "On the computation of the capacity region of the discrete MAC," *IEEE Transactions on Communications*, vol. 58, pp. 3512–3525, Dec 2010.
- [68] W. Liu, S. Shen, D. H. K. Tsang, R. K. Mallik, and R. Murch, "An efficient ratio detector for ambient backscatter communication," *arxiv:2210.09920*, Oct 2022.