Joint Antenna Selection and Beamforming for an IRS Aided IoT System

Adit Jain, Rimalapudi Sarvendranath, *Member, IEEE* and Salil Kashyap, *Member, IEEE*

***Abstract*—Intelligent reflecting surface (IRS), which is made up of passive reflective elements and can control the phase of the incident signal, and antenna selection (AS) can be combined to yield a cost-and energy-efficient wireless technology for the Internet of Things (IoT) system. For an IRS-assisted IoT system with one fusion node and multiple sensor nodes, we develop a jointly optimal AS and passive beamforming rule that maximizes the sum data rate. In it, the number of required channel estimations increases linearly with the number of sensor nodes. Additional novel contributions include a closed-form AS and passive beamforming rule, which maximizes the sum of absolutes of channel gains while significantly reducing computational complexity. To further simplify, we propose a new channel acquisition procedure for which the number of channel estimations is independent of the number of sensor nodes. Our simulations show that the optimal rule yields up to $13.6\times$ and $6\times$ higher rates than the maximum channel gain based and block coordinate descent based algorithms, respectively. Furthermore, they show that the simpler AS rule yields up to $12.4\times$ gain compared to other AS rules in the literature and is robust to estimation errors.**

***Index Terms*—Intelligent reflecting surface, antenna selection, passive beamforming, IoT.**

I. Introduction

The Internet of Things (IoT) networks in which the sensors deployed over a large area communicate to a fusion node play a key role in several applications such as smart cities and precision agriculture [1], [2]. Operating these networks with ultra-low power consumption at sensors and fusion node is essential. The emerging intelligent reflecting surfaces (IRS), which can improve the wireless signal strength in the desired direction, can help the fusion node or the sensor nodes to transmit with lower power. Therefore, the IRS, which is made up of a large number of configurable passive reflective elements and controls the gain and phase of the reflected signal to achieve passive beamforming, can be deployed to improve the energy efficiency of the IoT networks [3].

Similar to IRS, transmit antenna selection (AS), in which a transmitter equipped with multiple antennas and a single radio frequency (RF) chain selects an antenna and connects to the available RF chain, also reduces cost and power consumption. It is shown to achieve diversity equal to the number of antennas even with less RF hardware, which made it a part of many wireless standards [4]. Furthermore, AS also reduces analog circuit design complexity and digital signal processing [5].

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Joint optimization of transmit precoding matrices and the IRS phase shifts to maximize the achievable data rate of an IRS-assisted IoT network is done in [1]. Furthermore, [2] considered the weighted sum rate maximization of an IRS-assisted IoT network.

Single User [5], [6]: For a single user system, jointly optimal AS and passive beamforming rule is derived in [5]. Furthermore, simpler rules with lower computational complexity and pilot transmission overhead were proposed. Similarly, a discrete cuckoo algorithm based AS was proposed for perfect channel state information (CSI) in [6].

Multiple Users [7]–[9]: For a multiple user system, joint AS and passive beamforming to maximize the sum data rate was studied using successive-refinement optimization in [7], using successive convex approximation (SCA) in [8], and block coordinate descent (BCD) approach in [9]. These AS algorithms require complete CSI. The algorithm in [7] performs AS and passive beamforming to iteratively maximize the sum-rate under different CSI considerations. A Dinkelbach method based AS and SCA based passive beamforming was proposed in [8]. A greedy AS and BCD based passive beamforming algorithm was developed with different CSI assumptions in [9]. For a multiple IRS system, a manifold optimization (MO) based beamforming algorithm was proposed in [10]. An unsupervised learning based joint active and passive beamforming was developed in [11].

Focus and Contributions: We consider an IRS assisted IoT network made up of a fusion node and multiple single antenna sensor nodes. Here, the fusion node is equipped with multiple antennas and single RF chain to reduce cost and power consumption. It performs AS to send same message to all the users over a narrow band single carrier. This common message can be control information such as synchronization details and data aggregation strategies to the sensor nodes. Furthermore, it can be firmware update, which is common to all the sensor nodes.

For this system, we focus on joint optimization of antenna index at the fusion node and reflection coefficients at the IRS to maximize the data rate summed over all the sensor nodes. Since the same message is sent to all the users, the above sum rate need not consider interference due to transmission to multiple sensors. Firstly, we consider discrete IRS phase shifts as IRS elements in practice can only induce certain phase shifts. Secondly, we consider spatial correlation among the IRS channel gains [12]. Thirdly, we consider the impact of channel estimation errors and focus on developing AS rules with lower channel estimation overhead. These are different from [5], [8], [9], which consider continuous phase shifts and from [5], [7], [9], [13], which consider independent IRS channel gains. We also note that our objective is different from the multiuser sum rate considered in [7], [9]. This is because, in our system same message is sent to all the sensor nodes and the interference need not be considered unlike multiuser sum rate, where interference due to transmissions to other nodes need to be considered. Our problem formulation is in general suitable for any communication system. However, hardware limitations such as single RF chain at the fusion node and bandwidth constraints makes it more suitable for the IoT networks.

Our specific contributions are as follows: *1) Optimal AS Rule:* We employ MO to develop an AS algorithm that finds jointly optimal antenna index at the fusion node and reflection coefficients of the IRS that maximizes the sum rate of an IRS assisted IoT system. This algorithm converge to a locally optimal solution [14]. The choice of MO algorithm is inspired by its near-optimal performance with significantly lower complexity compared to branch-and-bound algorithm [15].

2) Absolute Sum Based Selection (ASBS) Rule: We also propose a closed-form and scalable ASBS rule that jointly optimizes the antenna index at the fusion node and IRS reflection coefficients to maximize approximate sum rate. It computes absolutes of the direct link channel gains and cascaded reflected link channel gains summed over the nodes. It then adds all these to obtain the metric of each antenna and selects the antenna that maximizes the metric. This rule requires significantly lower number of computations compared to the MO based optimal rule.

3) New Channel Estimation Scheme for ASBS Rule: Exploiting the fact that ASBS rule requires only channel gains summed over sensor nodes, we propose a new CSI acquisition protocol. With this new scheme, the number of channel estimations required to perform AS and passive beamforming become independent of the number of sensor nodes. The ASBS rule combined with this channel estimation scheme yields an approach with significantly lower complexity which is scalable in terms of nodes.

4) Results: Our performance benchmarking shows that the proposed optimal rule yields multiple fold improvement compared to the existing AS rules. They show that even ASBS rule performs significantly better than the rules in the literature while requiring fewer channel estimations. Our results also study the impact of imperfect CSI, channel correlation, and discrete phase shifts on the sum rate achieved by the proposed AS rules.

Comparison: We note that our AS rules are different from the maximum channel gain (MCG) rule and the iterative sum-rate maximization (ISM) rule proposed in [7] and the BCD based rule in [9]. MCG rule first selects the antennas at the transmitter for random IRS phase-shifts. Then similar to BCD based rule in [9], it successively refines one phase at a time. However, the proposed MO rule jointly optimizes antenna index and the IRS phase-shifts.

Organization of paper: Section II presents the system model and problem formulation. Section III describes optimal and low complexity selection algorithms. Section IV compares the performance of the proposed AS rules. Our conclusions are given in Section V.

Notations: Scalars are denoted by lower-case letters. Vectors and matrices are denoted by boldface lower-case and upper-case letters, respectively. For a complex number a, $|a|$, $\arg(a)$, and a^* denote its absolute value, phase, and conjugate, respectively. For a vector $\mathbf{x}$, $\mathbf{x}^{\mathrm{T}}$, $\mathbf{x}^H$ denote its transpose, conjugate transpose, respectively.

II. System Model and Problem Formulation

Figure 1 shows our system model. In it, a fusion node equipped with N_t antennas and one RF chain broadcasts data to K single antenna sensor nodes with the help of an IRS made up of N reflective elements. Let $\mathcal{A} = \{1, 2, \ldots, N_t\}$, $\mathcal{N} = \{1, 2, \ldots, N\}$, and $\mathcal{K} = \{1, 2, \ldots, K\}$ denote the set of antennas, the set of IRS elements, and the set of sensor nodes, respectively. The fusion node dynamically selects an antenna $a \in \mathcal{A}$ and switches it to the RF chain. It also computes the discrete phase shift from M available phase shifts,

$$\Delta_i \in \left\{0, \frac{2\pi}{M}, \frac{4\pi}{M}, \ldots, \frac{(M-1)2\pi}{M}\right\}, \ \forall\ i\ \in \mathcal{N}, \qquad (1)$$

and communicates them to the IRS through a dedicated control link. We consider unity gain independent of the phase shift configured for all the IRS elements. This is widely used in the literature for analytical tractability [7], [14], [16]. We note that in practice, amplitude gain of an IRS reflection coefficient is a function of the phase shift configured [17]. However, assuming that the gain is independent of the phase shift configured simplifies the problem at hand and yields negligible loss in the performance [5].

Let $h_{km} \in \mathbb{C}$ denote the complex channel gains from m^{th} antenna of the fusion node to the k^{th} sensor node. Let $f_{im} \in \mathbb{C}$ denote the complex channel gains from m^{th} antenna of the fusion node to the i^{th} IRS element. Let $g_{ki} \in \mathbb{C}$ denote the complex channel gain from the i^{th} IRS element to the k^{th} sensor node. The signal received at sensor node k, when the fusion node broadcasts a complex symbol s with transmit power P using antenna m, is given by

$$y_k = \sqrt{P}\left(h_{km} + \sum_{i=1}^{N} g_{ki} f_{im} e^{j\Delta_i}\right) s + z_k, \qquad (2)$$

where z_k is complex additive white Gaussian noise with variance σ^2.

A. Channel Model and CSI

Signal bandwidths used by typical IoT networks such as long range (LoRa) and Sigfox are of the order of few hundred kilo Hertz [18]. Therefore, we focus on single carrier transmission and consider a quasi-static narrow band channel model in which the channel gains remain constant and show frequency flat response. Furthermore, we consider time-division

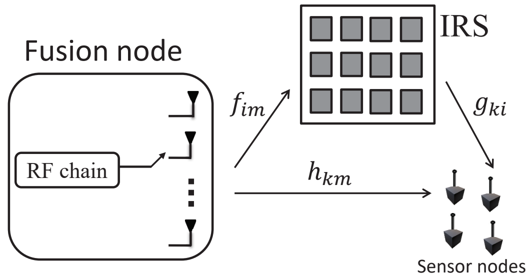

Figure 1. System model with an IRS assisted multi-antenna fusion node with single RF chain performing AS to send common data to multiple sensor nodes.

duplexing mode of operation to exploit channel reciprocity. We consider independent Rayleigh fading for the channel gains from the fusion node to sensor nodes and correlated Rician fading for the channels from the fusion node to IRS and from the IRS to sensor nodes. The sinc-function based channel correlation model developed in [12] is considered. The spatial correlation between the channel gains of the IRS elements n and m with spacing d_{nm} is modeled as $\frac{\sin(2\pi d_{nm}/\lambda)}{2\pi d_{nm}/\lambda}$, where λ denotes the wavelength. The sensor nodes transmit pilots and the fusion node estimates the direct link and reflected link channel gains using a two stage procedure described in [5], [16]. Let $\hat{h}_{km}$ and $\hat{c}_{kim}$ denote the estimates of the direct link channel gain h_{km} and cascaded link channel gains $c_{kim} = g_{ki} f_{im}$, respectively. Let $\tilde{h}_{km}$, and $\tilde{c}_{kim}$ denote the estimation errors of the direct link and cascaded link channel gains, respectively. We model them as in [7]:

$$\hat{h}_{km} = \sqrt{1-\sigma_e} h_{km} + \sqrt{\sigma_e} \tilde{h}_{km}, \tag{3}$$

$$\hat{c}_{kim} = \sqrt{1-\sigma_e} c_{kim} + \sqrt{\sigma_e}, \tilde{c}_{kim}, \tag{4}$$

$\forall\ k \in \mathcal{K}, \forall\ i \in \mathcal{N}, \forall\ m \in \mathcal{A}$, and $\sigma_e \in [0,1]$ captures the accuracy of channel estimation.

B. Problem Formulation

To avoid exhaustive search over all M^N combinations of discrete phases, we first consider a continuous phase $\theta_i \in [0, 2\pi]$ and then quantize it to obtain the discrete phase Δ_i. Let $x_i = e^{j\theta_i}, \forall\ i\ \in \mathcal{N}$ denote the reflection coefficient of the i^{th} IRS element, and $\mathbf{x} = [x_1^*, x_2^*, \ldots, x_N^*]^T \in \mathbb{C}^{N\times 1}$ denote the reflection coefficient vector. Therefore, the received signal in (2) becomes

$$y_k = \sqrt{P}\left(h_{km} + \sum_{i=1}^{N} c_{kim} x_i\right) s + z_k. \tag{5}$$

Let T_c and T_p denote the total number of symbols in the coherence interval and the number of pilot symbols, respectively. Let $\mathbf{c}_{km} = [c_{k1m}, c_{k2m}, \ldots, c_{kNm}]^T$ denote the vector of cascaded channel gains. From (5), the data rate summed over all the sensor nodes, for m^{th} antenna at the fusion node and the reflection coefficient vector $\mathbf{x}$, can be written as

$$R(m,\mathbf{x}) = \frac{T_c - T_p}{T_c} \sum_{k=1}^{K} \log_2\left(1 + \frac{P\left|h_{km} + \mathbf{x}^H \mathbf{c}_{km}\right|^2}{\sigma^2}\right). \tag{6}$$

We note that there is no interference term in the above sum rate expression as same data symbol s is sent from the fusion node to all the sensors.

Our goal is to jointly optimize the transmit antenna index m and the passive beamforming vector $\mathbf{x}$ to maximize the data rate summed over all the sensor nodes subject to unit modulus constraint of the IRS reflection coefficients. It can be mathematically stated as

$$\mathcal{P}: \quad \max_{m,\mathbf{x}} \quad R(m,\mathbf{x}), \tag{7}$$

$$\text{s.t.} \quad |x_i| = 1,\ \forall\ i \in \mathcal{N}. \tag{8}$$

In the next section, we propose an algorithm to solve the above problem $\mathcal{P}$, which is non-convex and is hard to solve due to unit modulus constraints.

III. Antenna Selection Algorithms

In this section, we will first propose an MO based algorithm, which yields a local optimal solution to $\mathcal{P}$ [14], and study its channel estimation overhead and computational complexity. We then propose an AS rule that significantly reduces the complexity. For it, we also propose a new channel estimation protocol that reduces estimation overhead.

A. MO Selection Algorithm

Let $D_{km}(\mathbf{x}) = P\left|h_{km} + \mathbf{x}^H \mathbf{c}_{km}\right|^2/\sigma^2$ denote the instantaneous signal-to-noise ratio from the m^{th} antenna of the fusion node to the k^{th} sensor node. For a given antenna $m \in \mathcal{A}$, the optimal passive beamforming vector $\mathbf{x}$ is the one that solves the following problem:

$$\mathcal{P}_m: \quad \max_{\mathbf{x}} \quad \sum_{k=1}^{K} \log_2\left(1 + D_{km}(\mathbf{x})\right), \tag{9}$$

$$\text{s.t.} \quad |x_i| = 1,\ \forall\ i \in \mathcal{N}. \tag{10}$$

In spite of being non-convex, the unit modulus constraints in (10) forms a complex circle manifold, which is a space that resembles an Euclidean space locally [5], [14]. This combined with differentiable nature of the objective function helps us solve $\mathcal{P}_m$.

In Euclidean space, to solve the optimization problem, we compute the gradient of the objective function, which indicates the direction in which the function increases. The structure of the unit modulus constraint helps us find an Euclidean gradient equivalent vector. For complex circle manifold, we obtain this by projecting the Euclidean gradient onto the tangent space at the point where we computed the Euclidean gradient. The Euclidean gradient of the objective function in (9) is given by

$$\sum_{k=1}^{K} \frac{1}{1 + D_{km}(\mathbf{x})} \nabla_{\mathbf{x}} D_{km}(\mathbf{x}), \tag{11}$$

where $\nabla_{\mathbf{x}} D_{km}(\mathbf{x}) = 2\mathbf{c}_{km}\mathbf{c}_{km}^H \mathbf{x} + 2h_{km}^* \mathbf{c}_{km}$. Using the projection of this vector, we can solve $\mathcal{P}_m$ using the optimization algorithms equivalent to the algorithms such as conjugate-gradient and trust-region developed for Euclidean space, which are shown to converge to a local optimal solution.

The optimal selection algorithm solves $\mathcal{P}_1, \ldots, \mathcal{P}_{N_t}$ using MO techniques to obtain the corresponding optimal passive beamforming vectors $\mathbf{x}_1, \ldots, \mathbf{x}_{N_t}$. It then selects antenna

$$a = \underset{m \in \{1, \ldots, N_t\}}{\arg\max} \; R\left(m, \mathbf{x}_m\right), \tag{12}$$

at the fusion node. It then Quantizes phases of $\mathbf{x}_a$ and sends them to the IRS. These steps are explained in detail in Algorithm 1.

Algorithm 1 Manifold Optimization Based Algorithm

1: Obtain required CSI
2: **for all** $m \in \mathcal{A}$ **do**
3: Solve $\mathcal{P}_m$ to obtain corresponding optimal passive beamforming vectors $\mathbf{x}_m$.
4: **end for**
5: Select antenna $a = \arg\max_{m \in \{1, \ldots, N_t\}} R\left(m, \mathbf{x}_m\right)$,
6: Quantize phases of $\mathbf{x}_a$ to obtain $\Delta_1, \ldots, \Delta_N$.
7: **return** $a, \Delta_1, \ldots, \Delta_N$.

Estimation Overhead and Computational Complexity of the MO Algorithm: Since, there is only one RF chain at the fusion node, each sensor node needs to send one pilot for each antenna at the fusion node to obtain the corresponding direct link channel gain. Therefore, the fusion node does KN_t estimations to obtain all the direct link channel gains. Similarly, each sensor node needs to send one pilot for each antenna at the fusion node and for each reflective element at the IRS to obtain cascaded reflected link channel gains. So, we need KN_tN estimations at the fusion node to obtain the reflected link CSI. Therefore, the total number of estimations required to obtain complete CSI is $KN_t(N+1)$, which increases as the number of sensor nodes increase.

Computational complexity of solving $\mathcal{P}_m$ using conjugate gradient algorithm is $\mathcal{O}\left(KN^{1.5}\right)$ [14]. Therefore, we need $\mathcal{O}\left(N_tKN^{1.5}\right)$ computations to solve $\mathcal{P}_1, \ldots, \mathcal{P}_{N_t}$. It scales better than the SCA and BCD algorithms considered in the literature [8], [9].

B. Absolute Sum Based Selection (ASBS)

We now propose the ASBS rule aimed at reducing the complexity of the MO algorithm. By Jensen's inequality, we know that

$$R\left(m, \mathbf{x}\right) \le K \frac{T_c - T_p}{T_c} \log_2\left(1 + \frac{P S_K\left(m, \mathbf{x}\right)}{K\sigma^2}\right), \tag{13}$$

where

$$S_K\left(m, \mathbf{x}\right) = \sum_{k=1}^{K} \left| h_{km} + \sum_{i=1}^{N} c_{kim} x_i \right|^2 \tag{14}$$

is the sum of absolute squares of the effective channel gains from the fusion node to the sensor nodes. Let $L_K\left(m, \mathbf{x}\right)$ denote the sum of absolutes of the effective channel gains, i.e.,

$$L_K\left(m, \mathbf{x}\right) = \sum_{k=1}^{K} \left| h_{km} + \sum_{i=1}^{N} c_{kim} x_i \right|. \tag{15}$$

Let

$$R_L(m, \mathbf{x}) = K \frac{T_c - T_p}{T_c} \log_2\left(1 + \frac{P\left(L_K\left(m, \mathbf{x}\right)\right)^2}{K\sigma^2}\right). \tag{16}$$

Using the fact that $S_K\left(m, \mathbf{x}\right) \le \left(L_K\left(m, \mathbf{x}\right)\right)^2$, we get $R\left(m, \mathbf{x}\right) \le R_L(m, \mathbf{x})$. From triangular inequality, we know

$$L_K\left(m, \mathbf{x}\right) \ge \left| \sum_{k=1}^{K} h_{km} + \sum_{k=1}^{K} \sum_{i=1}^{N} c_{kim} x_i \right|. \tag{17}$$

Substituting, the right hand side of (17) in (16) yields a lower bound on $R_L(m, \mathbf{x})$ and an approximation to the sum rate $R\left(m, \mathbf{x}\right)$. Therefore, we maximize $\left|\sum_{k=1}^{K} h_{km} + \sum_{i=1}^{N} x_i \sum_{k=1}^{K} c_{kim}\right|$ instead, which in turn maximizes the approximate sum rate. This approximation can be shown to be tight due to sum over large number of IRS elements. Thus, the simplified optimization problem can be written as

$$\mathcal{P}_L: \quad \max_{m, \mathbf{x}} \quad \left| \sum_{k=1}^{K} h_{km} + \sum_{i=1}^{N} x_i \sum_{k=1}^{K} c_{kim} \right|, \tag{18}$$

$$\text{s.t.} \quad |x_i| = 1, \; \forall \; i \in \; \mathcal{N}. \tag{19}$$

For a given antenna m, the objective in $\mathcal{P}_L$ is maximized when

$$x_i = \exp\left(j \arg\left(\sum_{k=1}^{K} h_{km} \right) - j \arg\left(\sum_{k=1}^{K} c_{kim} \right) \right), \tag{20}$$

$\forall \; i \; \in \mathcal{N}$. Substituting this in the objective function in (18), we get $\left|\sum_{k=1}^{K} h_{km}\right| + \sum_{i=1}^{N} \left|\sum_{k=1}^{K} c_{kim}\right|$. Therefore, the ASBS rule that solves $\mathcal{P}_L$ is given by

$$a = \underset{m \in \{1, \ldots, N_t\}}{\arg\max} \left\{ \left| \sum_{k=1}^{K} h_{km} \right| + \sum_{i=1}^{N} \left| \sum_{k=1}^{K} c_{kim} \right| \right\}, \tag{21}$$

$$\theta_i = \arg\left(\sum_{k=1}^{K} h_{ka} \right) - \arg\left(\sum_{k=1}^{K} c_{kia} \right), \forall \; i \in \mathcal{N}. \tag{22}$$

It configures the phases of all the IRS elements such that the corresponding sum of cascaded link channel gains of the selected antenna, i.e., $\sum_{k=1}^{K} c_{kia}$, is aligned with the sum of the direct link channel gains, i.e., $\sum_{k=1}^{K} h_{ka}$. We quantize the above θ_i to obtain discrete phase shifts Δ_i.

C. New Channel Estimation Protocol for the ASBS rule

Below, we propose a new two stage channel estimation procedure for the ASBS rule. In the first stage, IRS is in fully absorption mode to estimate the direct link channel gains. Here, all the sensor nodes transmit the same pilot symbol d_p simultaneously with power P_p. The signal received at the m^{th} antenna of the fusion node is given by

$$y_m^p = \sqrt{P_p} \sum_{k=1}^{K} h_{km} d_p + w_m, \tag{23}$$

where w_m is the additive Gaussian noise. Using y_m^p, we estimate $\sum_{k=1}^{K} h_{km}$ directly.

Similarly, in the second stage for the reflected link channel gains, the sensor nodes transmit d_p with only one IRS element in reflection mode. The received pilot signal at m^{th} antenna for i^{th} IRS element is given by

$$y_{im}^p = \sqrt{P_p}\left(\sum_{k=1}^{K} h_{km}\right)d_p + \sqrt{P_p}\left(\sum_{k=1}^{K} c_{kim}\right)d_p + w_m, \quad (24)$$

Here, we first subtract the direct link channel gains obtained in the first stage and then estimate $\sum_{k=1}^{K} c_{kim}$ for $i \in \mathcal{N}$.

As fusion node estimates only the sum channel gains, it performs N_t estimations to obtain the direct link CSI. Similarly, to obtain the sum of the cascaded link channel gains, it does N estimations per antenna. In total, fusion node performs $N_t(N+1)$ estimations, which is independent of K.

Complexity of ASBS Rule With the New Channel Estimation Protocol We need $\mathcal{O}\left(NN_t + N_t \log_2(N_t)\right)$ computations to select antenna a in (21) and $\mathcal{O}\left(N\right)$ computations to obtain phase in (22). Therefore, the ASBS rule combined with the proposed new CSI acquisition procedure is scalable in terms of number of sensor nodes. Its computational complexity and estimation overhead are independent of the number of sensor nodes and significantly lower than the MO based optimal selection algorithm. They are also lower compared to the MCG rule, which requires $\mathcal{O}\left(NKM + N_t \log_2(N_t)\right)$ computations and $\mathcal{O}\left(NKN_t\right)$ estimations [7]. Table below shows the scalability of ASBS rule in terms of number of users

	Computational complexity	Training overhead
MO	$\mathcal{O}(KN_tN^{1.5})$	$KN_t(N+1)$
ASBS	$\mathcal{O}(NN_t + N_t\log_2(N_t))$	$N_t(N+1)$

IV. Numerical Results and Discussion

We firstly benchmark the performance of the proposed AS rules with AS rules in the literature. We then study the impact of number of sensor nodes, discrete phase shifts, imperfect CSI, and the channel correlation on the proposed AS rules. Our simulation setup is similar to the multiuser system considered in [19]. We consider a signal bandwidth of 1 MHz centered around 3 GHz. The coherence interval T_c and noise variance are taken to be 33 ms and -114 dBm, respectively. Rice factor for different sensor nodes is modeled as $13 - 0.03d$, where d is the distance, and the path loss exponent is taken to be 3.6 for the direct channel and 2.4 for channels to and from the IRS [12]. Let d_{irs} denote the size of each IRS element.

Figure 2 plots the objective function in (9) as a function of the number of sensor nodes for the proposed AS rules, the MCG rule in [7], and BCD based AS rule proposed in [9]. To do a fair comparison the multi-user interference is not considered during AS and while computing the objective for the MCG and BCD rules. The performance is shown for both continuous phase shifts ($M = \infty$) and discrete phase shifts ($M = 8$). We see that the proposed MO algorithm performs significantly better for all the values of K. For $K = 100$ and $N = 196$, it achieves $13.6\times$ and $6\times$ higher sum rate than the BCD and MCG rules, respectively. This gain is due to the joint optimization of all the IRS phase shifts. We only show the performance for $M = 8$ for MCG rule as it is designed only for discrete phase shifts. We see that the ASBS rule, which requires much lower number of computations and estimations, also performs significantly better than the BCD and MCG rules in literature. This is because of its design to optimize approximate sum rate. For $K = 100$ and $N = 196$, it achieves $12.4\times$ and $5.5\times$ higher sum rate than the BCD and MCG rules, respectively. We also see that the performance of $M = 8$ discrete phase shifts, which require 3 bits, is close to the performance of the ideal IRS with continuous phase shifts.

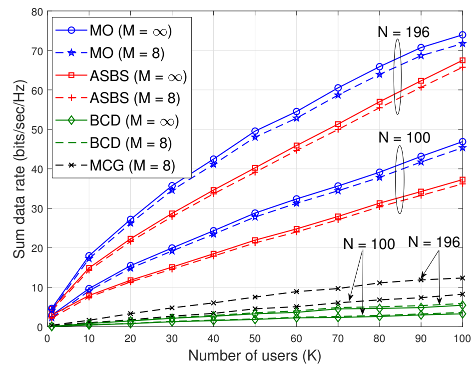

Figure 2. Impact of number of sensor nodes: Sum data rate as a function of number of sensor nodes ($N_t = 2$, $d_{irs} = \lambda/2$, $\sigma_e = 0$, and $P = 0$ dBm).

Figure 3 plots sum data rate as a function of the transmit power. It studies the impact of imperfect CSI on the proposed MO and ASBS rules. The sum data rate increases as the transmit power increases. We see that the performance of the ASBS rule with channel estimation errors is very close to the perfect CSI case. This negligible performance loss is due to the fact that the ASBS rule only estimates the sum channel gains and performs fewer channel estimations, i.e., $N_t(N+1)$. Thus the impact of estimation error is less for ASBS rule. Whereas the performance of the MO algorithm degrades significantly due to channel estimation errors. This is because it estimates cascaded channel gains corresponding to each IRS element for each user and performs $N_t(N+1)K$ estimations, which increase as the number of users increase. We note that the MCG and BCD rules also see an impact similar to the MO rule due to higher number of estimations. Thus, MO algorithm is sensitive to the estimation errors. In combination with Figure 2 we see that the ASBS rule is robust to channel estimation errors compared to the MO algorithm while performing reasonably well with significantly lower computational complexity.

Figure 4 studies the impact of IRS channel correlation. It plots the sum data rate as a function of power for the ASBS and MO rules. This is done for IRS element sizes of $d_{irs} = \lambda/2, \lambda/4$, and $\lambda/8$. We see an improvement in the sum data rate as the IRS element size decreases, which increases correlation among the channel gains of the IRS elements. This is inline with the observation in [20].

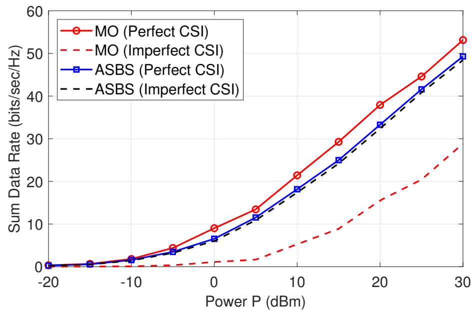

Figure 3. Impact of imperfect CSI: Sum data rate as a function of P ($N = 100, N_t = 4, K = 5$, and $\sigma_e = 10^{-14}$).

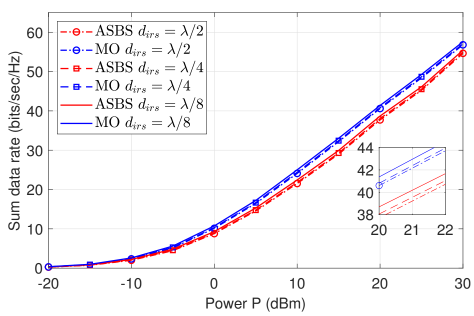

Figure 4. Impact of correlation: Sum data rate as a function of P ($N = 100, N_t = 4$, and $K = 5$).

V. Conclusions

We proposed a joint single AS and passive beamforming algorithm to maximize sum data rate of an IRS assisted IoT system. It employs MO techniques and converges to a locally optimal solution. For it, we showed that the number of channel estimations performed at the fusion node increase linearly as the number of sensor nodes increase. We also developed a simpler ASBS rule, which maximizes the approximate sum rate and is a function of channel gains summed over sensor nodes. Exploiting this, we developed a new CSI acquisition procedure in which the number of estimations required is independent of the number of sensor nodes. Our results showed that the proposed MO rule yields significant performance gain compared to the MCG and BCD based rules in the literature. Performance comparison showed that the ASBS rule performs well with significantly lower complexity. Furthermore, it is robust to the estimation errors as it performs fewer estimations compared to the MO algorithm. Therefore the proposed algorithms are both scalable and practical. Our results also showed that spatial correlation of IRS channels yields a slight improvement in the sum rate and discrete phase shifts with few bits are sufficient to reach the performance of the continuous phase shifts. Future work includes analysis of the energy savings and real-world tests of the IRS assisted AS system.

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