JOINT TRANSMIT PRECODERS AND PASSIVE REFLECTION BEAMFORMER DESIGN IN IRS-AIDED IOT NETWORKS

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ABSTRACT

This work considers an IoT network comprising of several IoT sensor nodes (SNs), a passive intelligent reflecting surface (IRS), and a fusion center (FC). Each IoT SN observes multiple physical phenomena, and transmits its observations to the FC for post processing. This necessitates the need for efficient preprocessing of each SN's observations to combat wireless fading effects and optimize transmit power utilization. In this context, this paper presents a novel approach that jointly designs the transmit precoding matrix (TPM) for IoT SNs and optimizes the phase reflection matrix (PRM) for the IRS. The resulting non-convex optimization problem is tackled through an alternating optimization framework, where the individual TPM and PRM design subproblems are further addressed using the majorization minimization (MM) framework. Notably, the proposed solution yields closed-form expressions for TPM and PRM in each MM iteration, making it particularly suitable for low-cost IoT SNs. Numerical results demonstrate the efficacy of the proposed approach by showcasing significant enhancements in estimation performance compared to IoT networks lacking an IRS component.

***Index Terms*—** Coherent MAC, IoT network, transmit precoding, intelligent reflecting surface, majorization minimization.

1. INTRODUCTION

The advent of internet of things (IoT) networks is catalyzing profound changes across industries. Over 75 billion IoT-connected gadgets are expected by 2025, transforming operations, urban living, healthcare, and everyday life. In conventional IoT networks, a number of IoT sensor nodes (SNs) are deployed in a geographical area to monitor or sense the unknown quantity of interest. Since, IoT SNs are low cost devices, they transmit their observations over a wireless channel to the central entity called fusion center (FC) for the receive processing. Hence, in order to transmit these observations efficiently, it becomes necessary to pre-process the IoT SNs' observations optimally. A summary of existing works in this context is presented next.

The problem of transceiver design for parameter estimation in an IoT network was first explored in the seminal work by Xiao *et al.* [1] where new schemes were proposed for the estimation of both scalar as well as vector parameters. However, the authors did not provide transceiver design for vector parameter estimation when the noise at the FC is present. This shortcoming was overcome by considering more general scenarios in [2] and [3] where alternate minimization based transceiver designs were developed. An innovative minimum variance distortionless precoding (MVDP) framework was proposed in [4] for unbiased parameter estimation, which does not require a combiner at the FC. Authors in [5] have proposed an interesting collaboration framework where the SNs prior to transmitting their observations to the FC, collaborates themselves and then transmits the cumulative observations to the FC. Taking this paradigm forward. authors of [6, 7] have developed SN collaboration strategy for temporally correlated and sparsity aware scenarios, respectively. The authors of [8–12] studied the problem of transceiver design in an energy harvesting IoT networks where the SNs run on the energy harvested from the radio frequency signals transmitted by different access points. Transceiver design in massive multiple input multiple output (MIMO) IoT networks was also explored in [13–15] where the FC is equipped with a large number of antennas. Authors of [16, 17] have proposed majorization theory based non-iterative transceiver designs for the IoT network considering perfect and imperfect channel state information (CSI) availability, respectively. Authors in [18] considered the problem of estimating a dynamic parameter under both total and individual sensor power limitations. Singh and Rajawat [19] proposed a scheme for the transceiver design of a time varying vector parameter such that the MSE is minimized at the FC subject to individual SN power constraint. Furthermore, the authors of [20] proposed both decentralised and distributed sequential linear minimum mean square error (LMMSE) techniques for static and dynamic vector parameter estimation, using time-varying channel and observation matrices. Joint collaboration and compression design for estimation and detection in IoT networks was studied in [21] and [22], respectively. Recently, the authors of [23, 24] studied parameter estimation in mmWave MIMO IoT networks relying on imperfect CSI. An interesting integrated sensing communication and computation framework is developed in [25] for the IoT network. However, none of the works mentioned above considered the scenario when IRS is employed to increase signal strength at the FC.

Ahmed *et. al* [26] were the first to study the IRS-aided IoT network and developed joint transmit and reflective beamforming design for secure estimation of a parameter in the presence of an eavesdropper. Further, a novel decision fusion strategy is devised in [27] for an IRS-aided sensor network. However, the use of IRS to enhance the parameter estimation accuracy is yet to be studied, and is the main objective of this work. In order to improve estimation accuracy, we develop a novel joint TPM and PRM design using alternate minimization to yield the minimum MSE. The individual TPM and PRM design problems are also non-convex in nature, which are solved using the popular majorization minimization (MM) framework [28]. Inspite of the coupling of the various TPMs, our design decouples it into a simple optimization problem for each IoT SN. Finally, our solution provides closed-form expressions for the optimal TPMs and PRM in each MM iteration which is well suited for IoT networks.

Throughput the paper, the matrix $\mathbf{A} = \text{blkdiag}(\mathbf{A}_1, \mathbf{A}_2, \ldots, \mathbf{A}_N)$ represents a diagonal matrix $\mathbf{A}$ of size $N^2 \times N^2$ with the matrices

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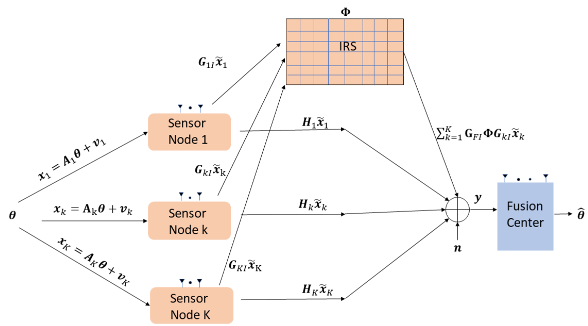

Fig. 1. System model for parameter sensing and communication in IRS-aided IoT network.

$\mathbf{A}_i$, for $i = 1, 2, \ldots, N$ on its principal diagonal; The trace and expectation operators are denoted by Tr[.] and $\mathbb{E}[.]$, respectively; The transpose, Hermitian and complex conjugate operations are denoted by $(.)^T$, $(.)^H$ and $(.)^*$, respectively; $\mathbf{a} \sim \mathcal{CN}(\mathbf{0}, \mathbf{R}_a)$ represents the circularly symmetric complex Gaussian distribution with mean zero and covariance matrix $\mathbf{R}_a$; $\mathbf{a}(i)$ and $\mathbf{A}(i, j)$ represent the ith and (i, j)th elements of the $\mathbf{a}$ and $\mathbf{A}$, respectively.

2. SYSTEM MODEL AND PROBLEM FORMULATION

Fig. 1 depicts an IRS-assisted IoT network, where the multi-antenna IoT SNs acquire linear observations of the underlying unknown vector parameter $\boldsymbol{\theta} \sim \mathcal{CN}(\mathbf{0}, \mathbf{R}_\theta) \in \mathbb{C}^{m\times 1}$. The observation vector $\mathbf{x}_k \in \mathbb{C}^{l_k \times 1}$ corresponding to the kth SN is given as

$$\mathbf{x}_k = \mathbf{A}_k \boldsymbol{\theta} + \mathbf{v}_k, \tag{1}$$

where $\mathbf{A}_k \in \mathbb{C}^{l_k\times m}$ represents the observation matrix corresponding to the kth SN, and $\mathbf{v}_k \sim \mathcal{CN}(\mathbf{0}, \mathbf{R}_{v_k} = \sigma_v^2 \mathbf{I}_{l_k}) \in \mathbb{C}^{l_k\times 1}$ represents the observation noise corresponding to the kth SN. In order to combat the adverse effects of fading wireless channels and to use the available transmit power at each SN effectively, one needs to precode the observation vector using the precoding matrix $\mathbf{F}_k \in \mathbb{C}^{N_t \times l_k}$, and the precoded observation used for transmission is $\tilde{\mathbf{x}}_k = \mathbf{F}_k \mathbf{x}_k$. Hence, the average transmit power of the kth SN is

$$\mathbb{E}\left[||\mathbf{F}_k \mathbf{x}_k||_2^2\right] = \text{Tr}\left[\mathbf{F}_k\left(\mathbf{A}_k \mathbf{R}_\theta \mathbf{A}_k^H + \mathbf{R}_{v_k}\right)\mathbf{F}_k^H\right] = P_k, \tag{2}$$

where P_k is the transmit power of the kth SN. Next, each IoT SN in the network transmits its precoded observation vector over a coherent multiple access channel (MAC), where all the IoT SNs are assumed to be synchronized such that their precoded signals reach as a coherent sum at the FC, which is mathematically represented as

$$\mathbf{y} = \sum_{k=1}^{K} \widetilde{\mathbf{H}}_k \mathbf{F}_k \mathbf{A}_k \boldsymbol{\theta} + \sum_{k=1}^{K} \widetilde{\mathbf{H}}_k \mathbf{F}_k \mathbf{v}_k + \mathbf{n}, \tag{3}$$

where $\mathbf{n} \sim \mathcal{CN}(\mathbf{0}, \mathbf{R}_n = \sigma_{fc}^2 \mathbf{I}_{N_r}) \in \mathbb{C}^{N_r\times 1}$ is the FC noise vector. Further, there are two possible paths through which the signals arrive at the FC, the direct path and the other through reflections from the IRS consisting of N passive reflection elements as shown in Fig. 1. The equivalent channel between the kth SN and the FC is $\widetilde{\mathbf{H}}_k = \mathbf{H}_k + \mathbf{G}_{FI} \boldsymbol{\Phi} \mathbf{G}_{kI} \in \mathbb{C}^{N_r\times N_t}$, where $\mathbf{H}_k \in \mathbb{C}^{N_r\times N_t}$ is the direct channel between the kth SN and the FC, while $\mathbf{G}_{kI} \in \mathbb{C}^{N\times N_t}$ is the channel between the kth SN and the IRS, $\boldsymbol{\Phi} \in \mathbb{C}^{N\times N}$ is the PRM, and finally $\mathbf{G}_{FI}$ is the channel matrix between the IRS and the FC. The received signal $\mathbf{y} \in \mathbb{C}^{N_r\times 1}$ at the FC can be given as

$$\mathbf{y} = \widetilde{\mathbf{H}}\mathbf{F}\mathbf{A}\boldsymbol{\theta} + \widetilde{\mathbf{H}}\mathbf{F}\mathbf{v} + \mathbf{n}, \tag{4}$$

where $\widetilde{\mathbf{H}} = [\widetilde{\mathbf{H}}_1, \widetilde{\mathbf{H}}_2, \ldots, \widetilde{\mathbf{H}}_K] \in \mathbb{C}^{N_r\times KN_t}$, $l = \sum_{k=1}^{K} l_k$, $\mathbf{F} =$ blkdiag $[\mathbf{F}_1, \mathbf{F}_2, \ldots, \mathbf{F}_K] \in \mathbb{C}^{KN_t\times l}$, and $\mathbf{A} = \left[\mathbf{A}_1^H, \mathbf{A}_2^H, \ldots, \mathbf{A}_K^H\right]^H \in \mathbb{C}^{l\times m}$. Using LMMSE combiner at the FC, the resulting expression for the MSE is [29]

$$\text{MSE} = \text{Tr}\left(\left(\mathbf{R}_\theta^{-1} + \mathbf{A}^H \widetilde{\mathbf{F}}^H \widetilde{\mathbf{R}}_n^{-1} \widetilde{\mathbf{F}} \mathbf{A}\right)^{-1}\right), \tag{5}$$

where $\widetilde{\mathbf{F}} = \widetilde{\mathbf{H}}\mathbf{F} \in \mathbf{C}^{N_r\times l}$, $\mathbf{R}_v = \text{blkdiag}\left(\mathbf{R}_{v_1}, \mathbf{R}_{v_2}, \ldots, \mathbf{R}_{v_K}\right) \in \mathbf{C}^{l\times l}$, $\widetilde{\mathbf{R}}_v = \left(\mathbf{R}_v + \mathbf{A}\mathbf{R}_\theta \mathbf{A}^H\right) \in \mathbf{C}^{l\times l}$ and $\widetilde{\mathbf{R}}_n = \widetilde{\mathbf{F}}\widetilde{\mathbf{R}}_v \widetilde{\mathbf{F}}^H + \mathbf{R}_n \in \mathbf{C}^{N_r\times N_r}$. The desired minimization of the MSE at the FC subject to individual SN power constraints, and the unit modulus constraint on the IRS elements can be formulated as follows.

$$\begin{aligned} \underset{\widetilde{\mathbf{F}}(\mathbf{F},\boldsymbol{\Phi})}{\text{minimize}} \quad & \text{Tr}\left(\left(\mathbf{R}_\theta^{-1} + \mathbf{A}^H \widetilde{\mathbf{F}}^H \widetilde{\mathbf{R}}_n^{-1} \widetilde{\mathbf{F}} \mathbf{A}\right)^{-1}\right) \\ \text{subject to} \quad & \text{Tr}\left[\mathbf{F}_k\left(\mathbf{A}_k \mathbf{R}_\theta \mathbf{A}_k^H + \mathbf{R}_{v_k}\right)\mathbf{F}_k^H\right] = P_k,\ 1 \le k \le K, \\ & \boldsymbol{\Phi}(i,i) = 1,\ 1 \le i \le N. \end{aligned} \tag{6}$$

This is a non-convex problem with the two design variables coupled. Hence, one needs to invoke the alternating optimization framework where TPMs and PRM will be designed in an iterative manner till convergence is achieved.

3. JOINT TRANSCEIVER-RIS BEAMFORMING DESIGN

This section discusses the joint design of TPMs and PRM wherein the alternating optimization framework to solve problem (7) is detailed. When the PRM is fixed, using the matrix inversion lemma [29] for the subproblem of TPM simplifies the MSE expression in (5) as

$$\text{MSE} = \text{Tr}\left[\mathbf{R}_\theta - \mathbf{R}_\theta \mathbf{A}^H \widetilde{\mathbf{F}}^H \left(\widetilde{\mathbf{F}}\widetilde{\mathbf{R}}_v \widetilde{\mathbf{F}}^H + \mathbf{R}_n\right)^{-1} \widetilde{\mathbf{F}}\mathbf{A}\mathbf{R}_\theta\right].$$

Alternatively, optimization can be rewritten as

$$\begin{aligned} \underset{\widetilde{\mathbf{F}},\mathbf{Q}}{\text{minimize}} \quad & \text{Tr}\left[\mathbf{R}_\theta - \mathbf{R}_\theta \mathbf{A}^H \widetilde{\mathbf{F}}^H \mathbf{Q}^{-1} \widetilde{\mathbf{F}}\mathbf{A}\mathbf{R}_\theta\right] \triangleq f(\widetilde{\mathbf{F}}, \mathbf{Q}) \\ \text{subject to} \quad & \text{Tr}\left[\mathbf{F}_k\left(\mathbf{A}_k \mathbf{R}_\theta \mathbf{A}_k^H + \mathbf{R}_{v_k}\right)\mathbf{F}_k^H\right] = P_k,\ 1 \le k \le K. \end{aligned} \tag{7}$$

where $\mathbf{Q} = \left(\widetilde{\mathbf{F}}\widetilde{\mathbf{R}}_v \widetilde{\mathbf{F}}^H + \mathbf{R}_n\right)$. The function $f(\widetilde{\mathbf{F}}, \mathbf{Q})$ is jointly concave in $(\widetilde{\mathbf{F}}, \mathbf{Q})$. Within the majorization-minimization (MM) framework, we have

$$\begin{aligned} f(\widetilde{\mathbf{F}}, \mathbf{Q}) \le\ & f(\widetilde{\mathbf{F}}_t, \mathbf{Q}_t) + \text{Tr}\left[\mathbf{P}_t^H \widetilde{\mathbf{F}}\mathbf{A}\mathbf{R}_\theta \mathbf{A}^H \widetilde{\mathbf{F}}^H \mathbf{P}_t\right] \\ & - 2\Re\left\{\text{Tr}\left[\mathbf{R}_\theta \mathbf{P}_t^H \widetilde{\mathbf{F}}\mathbf{A}\right]\right\}, \end{aligned} \tag{8}$$

where $\mathbf{P}_t = \left(\widetilde{\mathbf{F}}_t \widetilde{\mathbf{R}}_v \widetilde{\mathbf{F}}_t^H + \mathbf{R}_n\right)^{-1} \widetilde{\mathbf{F}}_t \mathbf{A}\mathbf{R}_\theta \in \mathbb{C}^{N_r\times m}$. Now, after substituting back $\widetilde{\mathbf{F}} = \widetilde{\mathbf{H}}\mathbf{F}$, defining $\mathbf{B} = \mathbf{P}_t^H \widetilde{\mathbf{H}}\mathbf{F}\mathbf{A}\mathbf{R}_\theta^{\frac{1}{2}}$ and ignoring the constant term, the majorized problem at the the tth MM iteration is

$$\begin{aligned} \underset{\mathbf{F}}{\text{minimize}} \quad & f(\mathbf{F}) \triangleq \text{Tr}\left[\mathbf{B}\mathbf{B}^H\right] - 2\Re\left\{\text{Tr}\left[\mathbf{R}_\theta \mathbf{P}_t^H \widetilde{\mathbf{F}}\mathbf{A}\right]\right\} \\ \text{subject to} \quad & \text{Tr}\left[\mathbf{F}_k\left(\mathbf{A}_k \mathbf{R}_\theta \mathbf{A}_k^H + \mathbf{R}_{v_k}\right)\mathbf{F}_k^H\right] = P_k,\ 1 \le k \le K. \end{aligned}$$

The optimization objective above can be reformulated as

$$f(\mathbf{F}) = \text{vec}(\mathbf{F})^H \left[\left(\mathbf{A}\mathbf{R}_\theta\mathbf{A}^H\right) \otimes \left(\widetilde{\mathbf{H}}^H\mathbf{P}_t\mathbf{P}_t^H\widetilde{\mathbf{H}}\right)\right] \text{vec}(\mathbf{F}) - 2\Re\left\{\text{vec}(\mathbf{F})^H \text{vec}(\widetilde{\mathbf{H}}^H\mathbf{P}_t\mathbf{R}_\theta\mathbf{A}^H)\right\}$$

Using the following relations, one can say that

$$\underbrace{\left(\left(\mathbf{A}\mathbf{R}_\theta\mathbf{A}^H + \mathbf{I}_K \otimes \mathbf{R}_v\right) \otimes (\lambda_t)\mathbf{I}_{KN_t}\right)}_{\mathbf{M}} \succeq \underbrace{\left(\mathbf{A}\mathbf{R}_\theta\mathbf{A}^H \otimes \widetilde{\mathbf{H}}^H\mathbf{P}_t\mathbf{P}_t^H\widetilde{\mathbf{H}}\right)}_{\mathbf{L}}$$

where $\lambda_t = \text{Tr}\left(\widetilde{\mathbf{H}}^H\mathbf{P}_t\mathbf{P}_t^H\widetilde{\mathbf{H}}\right)$. Furthermore, one can say that

$$\text{vec}(\mathbf{F})^H\mathbf{L}\text{vec}(\mathbf{F}) \preceq \text{vec}(\mathbf{F})^H\mathbf{M}\text{vec}(\mathbf{F}) + 2\Re\left\{\text{vec}(\mathbf{F})^H\left(\mathbf{L}-\mathbf{M}\right)\text{vec}(\mathbf{F}_t)\right\} + \text{Const. at point } \mathbf{F}_t$$

We can verify that $\text{vec}(\mathbf{F})^H\mathbf{M}\text{vec}(\mathbf{F}) = \lambda_t\sum_{k=1}^K P_k$. Thus, the majorization problem of Eq.(9) at the tth iteration of MM is

$$\begin{aligned}\underset{\mathbf{F}}{\text{minimize}} \quad & 2\Re\left\{\text{vec}(\mathbf{F})^H\left(\mathbf{L}-\mathbf{M}\right)\text{vec}(\mathbf{F}_t)\right\} \\ & -2\Re\left\{\text{vec}(\mathbf{F})^H\text{vec}(\widetilde{\mathbf{H}}^H\mathbf{P}_t\mathbf{R}_\theta\mathbf{A}^H)\right\} \triangleq g(\mathbf{F}) \\ \text{subject to} \quad & \text{Tr}\left[\mathbf{F}_k\left(\mathbf{A}_k\mathbf{R}_\theta\mathbf{A}_k^H + \mathbf{R}_v\right)\mathbf{F}_k^H\right] = P_k,\ 1 \le k \le K.\end{aligned}$$

The optimization objective $g(\mathbf{F})$ can be further simplified as

$$g(\mathbf{F}) = 2\Re\left\{\text{vec}(\mathbf{F})^H\mathbf{a}\right\} - 2\Re\left\{\text{vec}(\mathbf{F})^H\underbrace{\text{vec}(\widetilde{\mathbf{H}}^H\mathbf{P}_t\mathbf{R}_\theta\mathbf{A}^H)}_{\mathbf{b}}\right\} = 2\Re\left\{\text{vec}(\mathbf{F})^H(\mathbf{a}-\mathbf{b})\right\},$$

where $\mathbf{a} = (\mathbf{L}-\mathbf{M})\text{vec}(\mathbf{F}_t)$ can be further simplified as

$$(\mathbf{L}-\mathbf{M})\text{vec}(\mathbf{F}_t) = \mathbf{L}\text{vec}(\mathbf{F}_t) - \mathbf{M}\text{vec}(\mathbf{F}_t) = \text{vec}\left(\underbrace{\widetilde{\mathbf{H}}^H\mathbf{P}_t\mathbf{P}_t^H\widetilde{\mathbf{H}}\mathbf{F}_t\mathbf{A}\mathbf{R}_\theta\mathbf{A}^H - (\lambda_t\mathbf{F}_t(\mathbf{A}\mathbf{R}_\theta\mathbf{A}^H + \mathbf{I}_K \otimes \mathbf{R}_v)}_{\mathbf{E}}\right)$$

Hence $\mathbf{a}-\mathbf{b}$ can be written as

$$\mathbf{a}-\mathbf{b} = \text{vec}\left(\underbrace{\mathbf{E} - \widetilde{\mathbf{H}}^H\mathbf{P}_t\mathbf{R}_\theta\mathbf{A}^H}_{\widetilde{\mathbf{E}}}\right) = \text{vec}\left(\widetilde{\mathbf{E}}\right).$$

Thus, the optimization problem in (9) can be equivalently written as

$$\begin{aligned}\underset{\mathbf{F}}{\text{minimize}} \quad & \Re\left\{\text{Tr}\left[\widetilde{\mathbf{E}}^H\mathbf{F}\right]\right\} \\ \text{subject to} \quad & \text{Tr}\left[\mathbf{F}_k\left(\mathbf{A}_k\mathbf{R}_\theta\mathbf{A}_k^H + \mathbf{R}_v\right)\mathbf{F}_k^H\right] = P_k,\ 1 \le k \le K.\end{aligned}$$

The above optimization problem can be decomposed into K parallel subproblems, the kth one is

$$\begin{aligned}\underset{\mathbf{F}_k}{\text{minimize}} \quad & \Re\left\{\text{Tr}\left[\widetilde{\mathbf{E}}_k^H\mathbf{F}_k\right]\right\} \\ \text{subject to} \quad & \text{Tr}\left[\mathbf{F}_k\left(\mathbf{A}_k\mathbf{R}_\theta\mathbf{A}_k^H + \mathbf{R}_v\right)\mathbf{F}_k^H\right] = P_k, \end{aligned} \qquad (9)$$

where $\widetilde{\mathbf{E}}_k$ is defined as the kth block of the block-diagonal matrix $\widetilde{\mathbf{E}} = \text{blkdiag}\left[\widetilde{\mathbf{E}}_1, \widetilde{\mathbf{E}}_2, \ldots, \widetilde{\mathbf{E}}_K\right]$. The above optimization problem in (9) can be further simplified as

$$\begin{aligned}\underset{\mathbf{F}_k}{\text{minimize}} \quad & \Re\left\{\text{vec}\left(\widetilde{\mathbf{E}}_k\right)^H\text{vec}\left(\mathbf{F}_k\right)\right\} \\ \text{subject to} \quad & \text{vec}\left(\mathbf{F}_k\right)^H\left(\left(\mathbf{A}_k\mathbf{R}_\theta\mathbf{A}_k^H + \mathbf{R}_v\right)\otimes\mathbf{I}\right)\text{vec}\left(\mathbf{F}_k\right) = P_k.\end{aligned}$$

The optimal solution $\mathbf{F}_k^*$ for the above optimization problem is

$$\text{vec}\left(\mathbf{F}_k^*\right) = -\alpha_k^*\text{vec}\left(\widetilde{\mathbf{E}}_k\right),$$

where α_k^* are the optimum values where the power constraint is satisfied. It can be obtained as the solution of the following optimization problem

$$\alpha_k^* = \sqrt{\frac{P_k}{\text{vec}\left(\widetilde{\mathbf{E}}_k\right)^H\left(\left(\mathbf{A}_k\mathbf{R}_\theta\mathbf{A}_k^H + \mathbf{R}_v\right)\otimes\mathbf{I}\right)\text{vec}\left(\widetilde{\mathbf{E}}_k\right)}}. \qquad (10)$$

Solving the K sub-problems to obtain $\mathbf{F}_1^*, \mathbf{F}_2^*, \ldots, \mathbf{F}_K^*$, one can obtain the $\mathbf{F}^* = \text{blkdiag}\left(\mathbf{F}_1^*, \mathbf{F}_2^*, \ldots, \mathbf{F}_K^*\right)$. Subsequently, by substituting $\widetilde{\mathbf{F}} = \left(\mathbf{H} + \mathbf{G}_{FI}\mathbf{\Phi}\mathbf{G}_{IS}\right)\mathbf{F}$ the optimization objective to find the optimal reflection matrix $\mathbf{\Phi}$ is

$$\begin{aligned}&\text{Tr}\left[\mathbf{P}_t^H\left(\mathbf{H} + \mathbf{G}_{FI}\mathbf{\Phi}\mathbf{G}_{IS}\right)\mathbf{F}\mathbf{A}\mathbf{R}_\theta\mathbf{A}^H\mathbf{F}^H\left(\mathbf{H} + \mathbf{G}_{FI}\mathbf{\Phi}\mathbf{G}_{IS}\right)^H\mathbf{P}_t\right] \\ &- 2\Re\left\{\text{Tr}\left[\mathbf{R}_\theta\mathbf{P}_t^H\widetilde{\mathbf{F}}\mathbf{A}\right]\right\} = \text{Tr}\left[\mathbf{C}\mathbf{\Phi}^H\mathbf{D}\right] + \text{Tr}\left[\mathbf{D}^H\mathbf{\Phi}\mathbf{C}^H\right] \\ &+ \text{Tr}\left[\mathbf{B}\mathbf{B}^H\right] - 2\Re\left\{\text{Tr}\left[\mathbf{R}_\theta\mathbf{P}_t^H\mathbf{H}\mathbf{F}\mathbf{A}\right] + \text{Tr}\left[\mathbf{K}\mathbf{\Phi}\right]\right\} + \\ &+ \text{Tr}\left[\mathbf{D}^H\mathbf{\Phi}\mathbf{J}\mathbf{\Phi}^H\mathbf{D}\right],\end{aligned} \qquad (11)$$

where the different matrices are defined as

$$\begin{aligned}\mathbf{C} &= \mathbf{P}_t^H\mathbf{H}\mathbf{F}\mathbf{A}\mathbf{R}_\theta\mathbf{A}^H\mathbf{F}^H\mathbf{G}_{IS}^H \\ \mathbf{D} &= \mathbf{G}_{FI}^H\mathbf{P}_t \\ \mathbf{J} &= \mathbf{G}_{IS}\mathbf{F}\mathbf{A}\mathbf{R}_\theta\mathbf{A}^H\mathbf{F}^H\mathbf{G}_{IS}^H \\ \mathbf{S} &= \mathbf{G}_{FI}\mathbf{F}\mathbf{A}\mathbf{R}_\theta\mathbf{P}_t^H\mathbf{G}_{IS}.\end{aligned}$$

, Hence, the optimization problem to find $\mathbf{\Phi}$ is

$$\begin{aligned}\underset{\mathbf{\Phi}}{\text{minimize}} \quad & \text{Tr}\left[\mathbf{D}\mathbf{C}\mathbf{\Phi}^H\right] + \text{Tr}\left[\mathbf{C}^H\mathbf{D}^H\mathbf{\Phi}\right] + \text{Tr}\left[\mathbf{D}^H\mathbf{\Phi}\mathbf{J}\mathbf{\Phi}^H\mathbf{D}\right] \\ & -2\Re\left\{\text{Tr}\left[\mathbf{S}^H\mathbf{\Phi}\right]\right\} \\ \text{subject to} \quad & \mathbf{\Phi}(i,i) = 1,\ 1 \le i \le N.\end{aligned} \qquad (12)$$

where the constant terms are ignored. It can be further simplified as

$$\begin{aligned}\underset{\mathbf{\Phi}}{\text{minimize}} \quad & 2\Re\left\{\text{Tr}\left[\underbrace{\left(\mathbf{D}\mathbf{C} - \mathbf{S}\right)^H}_{\widetilde{\mathbf{S}}^H}\mathbf{\Phi}\right]\right\} + \text{Tr}\left[\mathbf{D}^H\mathbf{\Phi}\mathbf{J}\mathbf{\Phi}^H\mathbf{D}\right] \\ \text{subject to} \quad & \mathbf{\Phi}(i,i) = 1,\ 1 \le i \le N.\end{aligned} \qquad (13)$$

This can also be equivalently written as

$$\begin{aligned}\underset{\mathbf{\Phi}}{\text{minimize}} \quad & 2\Re\left\{\text{vec}\left(\widetilde{\mathbf{S}}\right)^H\text{vec}\left(\mathbf{\Phi}\right)\right\} + \text{vec}\left(\mathbf{\Phi}\right)^H\widetilde{\mathbf{J}}\text{vec}\left(\mathbf{\Phi}\right) \\ \text{subject to} \quad & \mathbf{\Phi}(i,i) = 1,\ 1 \le i \le N,\end{aligned} \qquad (14)$$

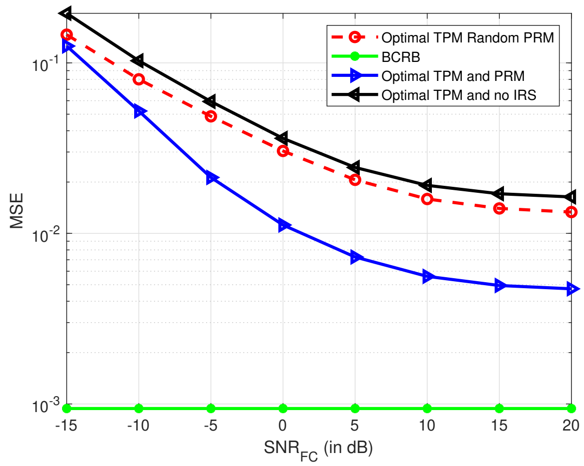

Fig. 2. MSE versus SNR_{FC} performance comparison with the BCRB

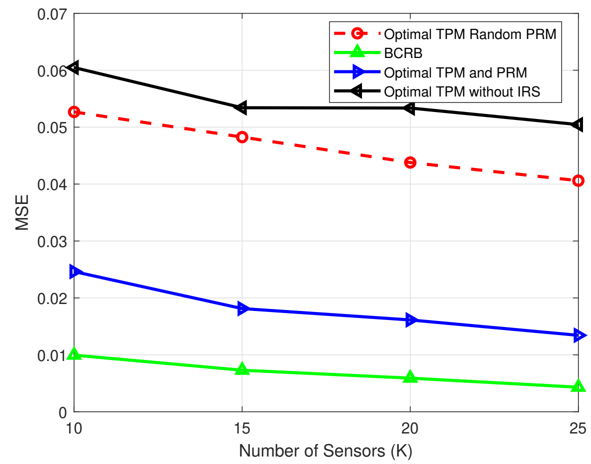

Fig. 3. MSE versus number of sensors K in the IoT network.

where $\text{vec}(\mathbf{\Phi}) = [\phi_1, 0, \ldots, 0, 0, \phi_2, \ldots, 0, 0, 0, \ldots, \phi_N]^T$, $\widetilde{\mathbf{J}} = \left(\mathbf{J}^H \otimes \mathbf{D}\mathbf{D}^H\right)$, and define $\boldsymbol{\phi} = [\phi_1, \phi_2, \ldots, \phi_N]^T \in \mathbb{C}^{N\times 1}$. We can always construct a matrix $\widehat{\mathbf{J}}$ such that

$$\boldsymbol{\phi}^H \widehat{\mathbf{J}} \boldsymbol{\phi} = \text{vec}(\mathbf{\Phi})^H \widetilde{\mathbf{J}} \text{vec}(\mathbf{\Phi}). \tag{15}$$

Similarly, one can write the term $2\Re\left\{\text{vec}\left(\widetilde{\mathbf{S}}\right)^H \text{vec}(\mathbf{\Phi})\right\}$ as

$$2\Re\left\{\text{vec}\left(\widetilde{\mathbf{S}}\right)^H \text{vec}(\mathbf{\Phi})\right\} = 2\Re\left\{\widehat{\mathbf{s}}^H \boldsymbol{\phi}\right\}, \tag{16}$$

where once can construct $\widehat{\mathbf{s}}$ from the vector $\text{vec}\left(\widetilde{\mathbf{S}}\right)$. Hence, finally the optimization problem can be written as

$$\begin{aligned} \underset{\boldsymbol{\phi}}{\text{minimize}} \quad & \boldsymbol{\phi}^H \widehat{\mathbf{J}} \boldsymbol{\phi} + 2\Re\left\{\widehat{\mathbf{s}}^H \boldsymbol{\phi}\right\} \\ \text{subject to} \quad & \boldsymbol{\phi}(i) = 1,\ 1 \le i \le N, \end{aligned} \tag{17}$$

Once again using the MM framework, this problem can be equivalently written as

$$\begin{aligned} \underset{\boldsymbol{\phi}}{\text{minimize}} \quad & \Re\left\{\widetilde{\mathbf{f}}^H \boldsymbol{\phi}\right\} \\ \text{subject to} \quad & \boldsymbol{\phi}(i) = 1,\ 1 \le i \le N, \end{aligned} \tag{18}$$

The optimal $\boldsymbol{\phi}$ can be obtained as $\boldsymbol{\phi} = -e^{j\arg(\widetilde{\mathbf{f}})}$. Next section presents the simulation results to verify the performance of the proposed design.

4. SIMULATION RESULTS

This section presents the results of a simulation-based study to validate the model and schemes described. In all experiments, we generate the channel coefficients as independent and identically distributed (i.i.d.) samples which follows the distribution $\mathcal{CN}(0,1)$. The path loss model is $\mu = (\frac{d}{d_0})^{-\nu}$ where $\mu = -30$ dB is the path loss at the reference distance of 1m. The path loss exponent ν is set to 2 for all SNs-to-IRS, and IRS-to-FC, and 3 for SNs to the FC links. The number of SNs in the MIMO IoT network is set to $K = 10$. The number of observations taken by each SN is $l_k = 3$, the number of antennas at each SN is $N_t = 3$, while the number of receive antennas at the FC is considered to be $N_r = 3$. The dimension of the unknown vector parameter $\boldsymbol{\theta}$ is $m = 3$. For simplicity, the observation noise covariance matrix $\mathbf{R}_{v_k}$ for each SN k and the FC noise covariance matrix $\mathbf{R}_n$ are considered as $\mathbf{R}_{v_k} = \sigma_v^2 \mathbf{I}_{l_k}$ and $\mathbf{R}_n = \sigma_n^2 \mathbf{I}_{N_r}$, where the quantities σ_v^2 and σ_n^2 denote the variances of the observation and FC noises, respectively. The signal-to-noise ratio (SNR) at the FC is defined as $\text{SNR}_{\text{FC}} = \frac{1}{\sigma_n^2}$. Similarly, the observation SNR denoted by SNR_{OB} is set to $\text{SNR}_{\text{OB}} = \frac{1}{\sigma_v^2}$. The Bayesian Cramer Rao bound (BCRB) is the MSE when all the observations are available directly at the FC without any loss, and the MMSE estimator is used to generate the estimate of $\boldsymbol{\theta}$ [16].

Fig. 2 plots the MSE against the SNR_{FC}. As anticipated, the MSE exhibits a downward trend as the SNR_{FC} rises. This may be attributed to the diminishing impact of noise as the SNR_{FC} grows, hence leading to enhanced MSE performance. In order to show the effectiveness of the IRS, we have also plotted the MSE performance with optimal TPMs and a random PRM, where the PRM is set to a random matrix. Also, the scenario when the IRS is absent is considered. For instance, at $\text{SNR}_{\text{FC}} = 5$ dB the proposed design has MSE $= 0.007$, while the design with optimal TPMs and random PRM has MSE $= 0.02$, and the optimal TPM without IRS has MSE $= 0.025$. Hence, the proposed design offers 4.56, and 5.53 dB lower MSE than optimal TPMs and random PRM and optimal TPMs without IRS, respectively. This shows the effectiveness of employing an IRS to improve MSE performance.

Fig. 3 depicts the MSE performance of the proposed scheme as a function of number of IoT SNs K in the network. It can be readily observed from the figure that as the number of sensors increases in the network, the MSE performance improves since more observations are available at the FC, which yields improved MSE performance. Once again, the MSE performance loss corresponding to the scenarios when we have optimal TPMs for each IoT SN while we use a random phase matrix for the IRS and optimal TPMs for each IoT SN without an IRS is clearly evident in the figure.

5. CONCLUSION

A joint TPMs and PRM design scheme has been developed for an IRS-assisted IoT network for the efficient estimation of the random vector parameter. Leveraging the MM algorithm the optimal TPMs and PRM were designed using an alternating optimization framework. Simulation results corroborate the analytical finding of this paper. Future works can consider IoT networks with quantized sensor measurement transmission, sensor collaboration, studying and exploiting the spatial as well as temporal correlation of the underlying elements in the unknown parameter vector.

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