Energy Efficient Massive MIMO IoT Network: A Power and MSE Constrained Approach

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***Abstract*—This paper considers massive multiple-input multiple-output (MIMO) Internet of Things (IoT) networks where each sensor is equipped with a single antenna, while the fusion center (FC) is equipped with a massive array of antennas. Each sensor takes the linear noisy observation of the underlying unknown random quantity, pre-processes it, and then transmits its precoded observation to the FC over a fading wireless channel for efficient post-processing. Since these sensors are battery-operated tiny devices, energy efficiency (EE) becomes such a critical factor to optimize, while individual mean square error (MSE)-based quality of service (QoS) constraints ensures an efficient estimation of the random quantities at the FC. Quadratic transform theory is used to solve the resulting non-convex EE maximization problem, and the first-order Taylor series approximation is used to linearize the non-convex quantities. Our numerical results corroborate the analytical findings of this work.**

***Index Terms*—parameter estimation, energy efficiency maximization, massive MIMO, quadratic transform, massive MIMO, Internet of things.**

I. Introduction

Internet of Things (IoT) networks enable various applications like environmental monitoring, smart healthcare, and autonomous homes. In order to practically realize all these applications, IoT networks need to rely on tiny single-antenna sensors, which will take the linear measurement of the underlying unknown quantity of interest. Since these tiny sensors are not able to perform efficient fusion of the observations due to their power and hardware limitations. Hence, they transmit their observations to a central entity called fusion center (FC), which does not have any power or hardware limitations. It collects the observations from all the sensors in the IoT network and efficiently combines them to obtain an efficient estimate of the underlying quantities of interest. Since the sensors transmit their observations over a wireless coherent multiple access channel (MAC), all the sensors are assumed to be synchronized in such a way that their observations reach a coherent sum at the FC. Next, we discuss the existing work in the literature related to parameter estimation in massive multiple-input multiple-output (MIMO) IoT networks.

Shirazinia *et al.* [1] have proposed two different schemes for efficient parameter estimation in a massive MIMO IoT network. First, minimizes the mean square error (MSE) subject to individual sensor power constraint while the second minimizes the total power consumption in the network while satisfying a threshold MSE constraint. Furthermore, it also includes the interesting analysis with correlated noise and channel. Ma *et al.* [2] have considered a wirelessly powered IoT network and developed a novel strategy for efficient date transfer where the FC is used as an energy access point as well as to fuse the data for the estimation. The authors of [3] have proposed an interesting framework with simultaneous wireless information and power transfer (SWIPT) in an IoT network. The use of a relay not only increases the physical range of communication but also splits the information into information and radio frequency (RF) power. A low-latency massive IoT access scheme is proposed by Li *et al.* in [4] for a mmWave extra-large (XL) MIMO network. Li *et al.* in [5] devised a grant-free multiple access in a massive MIMO IoT network where every device uses a preamble to reserve the channel along with data. However, all the above mentioned works have not consider the energy efficiency (EE maximization in an IoT network.

Lee [6] studies the problem of EE maximization in an orthogonal frequency division multiplexing (OFDM)-based massive MIMO industrial IoT (IIoT) network. A downlink scenario is considered where FC transmits the composite signal using orthogonal multiple access and signal clipping, while maximum ratio combining (MRC) and zero-forcing (ZF) combiners are used by the IoT sensors to recover their respective signals. However, our work considers an uplink scenario where sensors transmit their linearly precoded noisy observations to the FC, which is more suitable for an IoT network; otherwise, it is similar to a multi-user massive MIMO celluar network. Using the channel hardening property of a massive MIMO system, Lee in [7] has proposed a novel strategy for the reference signal overhead reduction to enable adaptive switching in an IIoT network. In [8] through systematic scheduling and optimal power control strategies connectivity is enhanced in a Massive IoT network. However, to the best of our knowledge, the EE maximization problem together with individual power and MSE-based quality of service (QoS) constraints in a massive MIMO IoT network is not being studied. This work tries to fill this research gap

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by maximizing the EE subject to individual sensor power and MSE constraints. Furthermore, to make the proposed design more practical, we use the imperfect channel estimate obtained from the minimum MSE (MMSE) channel estimation scheme to perform the MRC combining at the FC. Finally, the Quadratic transform (QT) theory is being employed to solve the fractional non-convex optimization problem. Our simulation results show the efficient performance of the proposed design against the equal power allocation. The next section describes the system model for parameter sensing and precoded observation transmission over a coherent MAC to the FC.

II. System Model for Parameter Sensing and Observation Transmission

As shown in Fig. 1, consider an IoT network where K sensors are deployed in a geographical area and each sensor k is sensing an unknown random parameter of interest, denoted by $\boldsymbol{\theta}_k \sim \mathcal{CN}(0, \sigma_k^2) \in \mathbb{C}$. The observation corresponding to the kth sensor denoted by $x_k \in \mathbb{C}$ can be mathematically modeled as $x_k = \theta_k + v_k$, where $v_k \sim \mathcal{CN}(0, \sigma_v^2) \in \mathbb{C}$ represents the observation noise. Subsequently, in order to combat the impediments arising due to wireless fading and the limited transmit power of the sensor, the observations corresponding to each sensor are pre-processed using the precoding coefficient $\alpha_k \in \mathbb{C}$ at each sensor k. The precoded observation is then transmitted over a coherent MAC to the FC for receiver processing. The FC is equipped with a large array of antennas, having $N >> K$ antennas. The received vector $\mathbf{y} \in \mathbb{C}^{N\times 1}$ at the FC can be modeled as

$$\mathbf{y} = \sum_{k=1}^{K} \mathbf{h}_k \alpha_k x_k + \mathbf{v}_{\text{FC}} = \sum_{k=1}^{K} \mathbf{h}_k \alpha_k \theta_k + \sum_{k=1}^{K} \mathbf{h}_k \alpha_k v_k + \mathbf{v}_{\text{FC}}. \tag{1}$$

The vector $\mathbf{h}_k \in \mathbb{C}^{N\times 1}$ and $\mathbf{v}_{\text{FC}} \sim \mathcal{CN}(0, \sigma_{fc}^2 \mathbf{I}_N) \in \mathbb{C}^{N\times 1}$ denote the wireless fading channel between the kth sensor and the FC, and the FC noise, respectively. The average transmit power constraint corresponding to the each sensor k is

$$\mathbb{E}\left[|\alpha_k x_k|^2\right] = |\alpha_k|^2(\sigma_k^2 + \sigma_v^2) \leq P_k, 1 \leq k \leq K, \tag{2}$$

where P_k denotes the transmit power budget of the kth sensor. The next section describes the MMSE-based channel estimation scheme for the channel vector between each sensor k and the FC.

III. MMSE Channel Estimation

In practice, the channel vector $\mathbf{h}_k \in \mathbb{C}^{N\times 1}$ for each sensor k is not known apriori and has to be estimated before estimating the parameter. This is done by transmitting pilot symbols from each sensor to the FC [9]. At the lth time instant, let $\mathbf{x}(l) = [x_1(l), x_2(l), \ldots, x_K(l)]^T \in \mathbb{C}^{K\times 1}$ denote the pilot vector to be transmitted by the sensors to the FC. The received pilot signal $\mathbf{y}_p(l) \in \mathbb{C}^{N\times 1}$ at the FC is

$$\mathbf{y}_p(l) = \sum_{k=1}^{K} \mathbf{h}_k x_k(l) + \mathbf{u}(l) = \mathbf{H}\mathbf{x}(l) + \mathbf{u}(l), \tag{3}$$

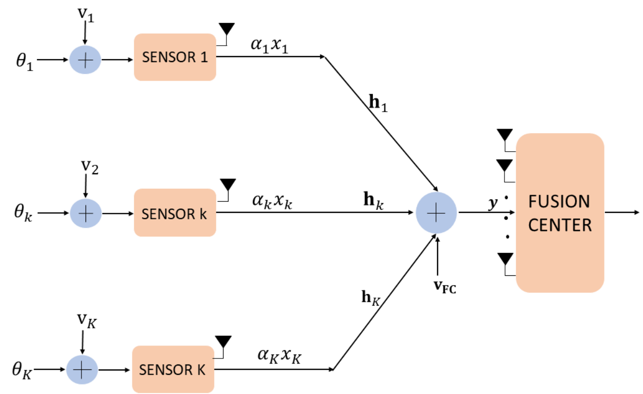


Fig. 1: System model for the parameter sensing and estimation in Massive MIMO IoT network.

where $\mathbf{u}(l) \in \mathbb{C}^{N\times 1}$ denotes the complex Gaussian pilot noise having zero mean and covariance matrix $\mathbf{R}_u = \sigma_u^2 \mathbf{I}_N$ and P_p is the pilot power. Furthermore, consider the transmission of $L \geqslant K$ pilots as $\mathbf{x}(1), \mathbf{x}(2), \cdots \mathbf{x}(L)$. The concatenated received matrix $\mathbf{Y} = [\mathbf{y}_p(1), \mathbf{y}_p(2), \ldots \mathbf{y}_p(L)] \in \mathbb{C}^{N\times L}$ at the FC is

$$\mathbf{Y} = \mathbf{H}\mathbf{X} + \mathbf{U}, \tag{4}$$

where $\mathbf{X} = [\mathbf{x}(1), \mathbf{x}(2), \cdots, \mathbf{x}(L)] \in \mathbb{C}^{K\times L}$ and $\mathbf{U} = [\mathbf{u}(1), \mathbf{u}(2), \cdots, \mathbf{u}(L)] \in \mathbb{C}^{N\times L}$. Multiplying the matrix $\mathbf{Y}$ with the kth pilot vector, one obtains

$$\widetilde{\mathbf{y}}_k = P_p \mathbf{h}_k + \widetilde{\mathbf{n}}_k. \tag{5}$$

Furthermore, employing MMSE combiner above [10], the LMMSE estimate $\widehat{\mathbf{h}}_k$ is

$$\widehat{\mathbf{h}}_k = \frac{\beta_k}{P_p\beta_k + \sigma_n^2}\widetilde{\mathbf{y}}_k. \tag{6}$$

The true channel is defined as $\mathbf{h}_k = \widehat{\mathbf{h}}_k + \mathbf{e}_k$, where $\mathbf{e}_k$ represents the estimation error vector, and it follows that

$$\mathbb{E}\left[\widehat{\mathbf{h}}_k \widehat{\mathbf{h}}_k^H\right] = \frac{P_p\beta_k^2}{P_p\beta_k + \sigma_n^2}\mathbf{I}_N, \mathbb{E}\left[\mathbf{e}_k\mathbf{e}_k^H\right] = \frac{\beta_k\sigma_n^2}{P_p\beta_k + \sigma_n^2}\mathbf{I}_N.$$

The next section formulates the EE maximization problem subject to individual sensor transmit power and MSE constraints.

IV. EE Maximization Problem Formulation Relying on Imperfect CSI

This section formally defines the EE along with other quantities which are useful in defining the EE. Toward this end, rewriting the received vector $\mathbf{y}$ in (1) at the FC as

$$\mathbf{y} = \underbrace{\mathbf{h}_k\alpha_k\theta_k}_{\text{DesiredSignal}} + \underbrace{\mathbf{h}_k\alpha_k v_k}_{\text{ObservationnoiseSignal}} + \underbrace{\sum_{l=1, l\neq k}^{K} \mathbf{h}_l\alpha_l\left(\theta_l + v_l\right)}_{\text{InterSensorInterference}} + \underbrace{\mathbf{v}_{\text{FC}}}_{\text{FCNoise}}. \tag{7}$$

Performing MRC combining using the estimated MMSE channel vector $\widehat{\mathbf{h}}_k$, the expression of estimate $\hat{\theta}_k = \widehat{\mathbf{h}}_k^H \mathbf{y}$ is

$$\widehat{\theta}_k = \widehat{\mathbf{h}}_k^H \widehat{\mathbf{h}}_k \alpha_k \theta_k + \sum_{l=1,l\neq k}^{K} \widehat{\mathbf{h}}_k^H \widehat{\mathbf{h}}_l^H \alpha_l \theta_l + \sum_{l=1}^{K} \widehat{\mathbf{h}}_k^H \mathbf{e}_l \alpha_l \theta_l + \sum_{l=1}^{K} \widehat{\mathbf{h}}_k^H \left(\widehat{\mathbf{h}}_l^H + \mathbf{e}_l\right) \alpha_l v_l + \widehat{\mathbf{h}}_k^H \mathbf{v}_{\text{FC}}. \quad (8)$$

It can also be equivalently written as

$$\widehat{\theta}_k = \mathbb{E}\left[\widehat{\mathbf{h}}_k^H \widehat{\mathbf{h}}_k\right] \alpha_k \theta_k + \left(\widehat{\mathbf{h}}_k^H \widehat{\mathbf{h}}_k - \mathbb{E}\left[\widehat{\mathbf{h}}_k^H \widehat{\mathbf{h}}_k\right]\right) \alpha_k \theta_k + \sum_{l=1,l\neq k}^{K} \widehat{\mathbf{h}}_k^H \widehat{\mathbf{h}}_l^H \alpha_l \theta_l + \sum_{l=1}^{K} \widehat{\mathbf{h}}_k^H \mathbf{e}_l \alpha_l \theta_l + \sum_{l=1}^{K} \widehat{\mathbf{h}}_k^H \left(\widehat{\mathbf{h}}_l^H + \mathbf{e}_l\right) \alpha_l v_l + \widehat{\mathbf{h}}_k^H \mathbf{v}_{\text{FC}}. \quad (9)$$

Furthermore, in a massive MIMO system the following simplification holds $\mathbb{E}\left[\left|\widehat{\mathbf{h}}_k^H \widehat{\mathbf{h}}_l\right|^2\right] = \frac{N P_p^2 \beta_k^2 \beta_l^2}{(P_p\beta_k+\sigma_n^2)(P_p\beta_l+\sigma_n^2)} = \Gamma_{lk}, \mathbb{E}\left[\left|\left|\widehat{\mathbf{h}}_k\right|\right|^2\right] = \frac{N P_p \beta_k^2}{(P_p\beta_k+\sigma_n^2)} = \eta_k, \text{Var}\left[\widehat{\mathbf{h}}_k^H \widehat{\mathbf{h}}_k\right] = \mathbb{E}\left[\left|\widehat{\mathbf{h}}_k^H \widehat{\mathbf{h}}_k\right|^2\right] - \left(\mathbb{E}\left[\left|\left|\widehat{\mathbf{h}}_k\right|\right|^2\right]\right)^2 = \frac{N(N+1) P_p^2 \beta_k^4}{(P_p\beta_k+\sigma_n^2)^2} - \frac{N^2 P_p^2 \beta_k^4}{(P_p\beta_k+\sigma_n^2)^2} = \frac{N P_p^2 \beta_k^4}{(P_p\beta_k+\sigma_n^2)^2} = V_k, \mathbb{E}\left[\left|\widehat{\mathbf{h}}_k^H \widehat{\mathbf{h}}_k\right|^2\right] = \frac{N(N+1) P_p^2 \beta_k^4}{(P_p\beta_k+\sigma_n^2)^2} = \delta_k, \mathbb{E}\left[\left|\widehat{\mathbf{h}}_k^H \mathbf{e}_k\right|^2\right] = \frac{\beta_k \sigma_n^2 \eta_k}{(P_p\beta_k+\sigma_n^2)} = \nu_k, \mathbb{E}\left[\left|\widehat{\mathbf{h}}_k^H \mathbf{e}_l\right|^2\right] = \frac{\beta_l \sigma_n^2 \eta_k}{(P_p\beta_l+\sigma_n^2)} = \zeta_{lk}$. Using these definitions, the corresponding SINR expression for this scenario can be evaluated as shown in (10), and the corresponding SE expression can also be derived using Eq. (13). Next section defines EE and formulates the EE maximization problem in detail. The advantage of this scheme is that the estimated channel is valid for a large coherence time and thus it reduces the overhead of the channel estimation. The sum SE (SSE) and the total power consumption (TPC) in the IoT network are defined as

$$\text{SSE} = \sum_{k=1}^{K} \left(\frac{T-\tau}{T}\right) \log_2\left(1 + \text{SINR}_k\right)$$
$$\text{TPC} = \left(\frac{T-\tau}{T}\right) \sum_{k=1}^{K} |\alpha_k|^2 (\sigma_k^2 + \sigma_v^2) + \frac{K\tau}{T} P_p + P_c,$$

where T is the total time elapsed in channel estimation and observation transmission, τ is the time required channel estimation, and TPC is composed of total average transmit power, total pilot power and total circuit power consumption, respectively. The $\text{EE} = \frac{\text{SSE}}{\text{TPC}}$ is defined as

$$\text{EE} = \frac{\sum_{k=1}^{K} \left(\frac{T-\tau}{T}\right) \log_2\left(1 + \text{SINR}_k\right)}{\left(\frac{T-\tau}{T}\right) \sum_{k=1}^{K} |\alpha_k|^2 (\sigma_k^2 + \sigma_v^2) + \frac{K\tau}{T} P_p + P_c}. \quad (11)$$

The normalized MSE of the kth sensor is $\text{MSE}_k = \mathbb{E}\left[|\widehat{\theta}_k - \theta_k|^2\right]$. Using the expression of $\widehat{\theta}_k$ in (9), the expression for MSE_k can be derived as

$$\text{MSE}_k = \sigma_v^2 + \frac{2\widehat{\mathbf{h}}_k^H \mathbf{e}_k}{||\widehat{\mathbf{h}}_k||^2} \sigma_v^2 + \frac{\widehat{\mathbf{h}}_k^H \mathbf{e}_k \mathbf{e}_k^H \widehat{\mathbf{h}}_k}{||\widehat{\mathbf{h}}_k||^4} (\sigma_k^2 + \sigma_v^2) + \sum_{l=1,l\neq k}^{K} \frac{\widehat{\mathbf{h}}_k^H \left(\widehat{\mathbf{h}}_l + \mathbf{e}_l\right)\left(\widehat{\mathbf{h}}_l + \mathbf{e}_l\right)^H \widehat{\mathbf{h}}_k}{\alpha_k^2 ||\widehat{\mathbf{h}}_k||^4} \alpha_l^2 (\sigma_l^2 + \sigma_v^2) + \frac{\sigma_{\text{FC}}^2}{\alpha_k^2 ||\widehat{\mathbf{h}}_k||^2}.$$

Using the following results $\mathbb{E}\left[\frac{1}{||\widehat{\mathbf{h}}_k||^2}\right] = \frac{(P_p\beta_k+\sigma_n^2)}{(N-1)P_p\beta_k^2}, \mathbb{E}\left[\mathbf{e}_k \mathbf{e}_k^H\right] = \frac{\beta_k \sigma_n^2}{P_p\beta_k+\sigma_n^2} \mathbf{I}_N, \mathbb{E}\left[\widehat{\mathbf{h}}_k \widehat{\mathbf{h}}_k^H\right] = \frac{P_p\beta_k^2}{P_p\beta_k+\sigma_n^2} \mathbf{I}_N$, the expression for the ergodic MSE which is defined as $\overline{\text{MSE}}_k = \mathbf{E}_{\widehat{\mathbf{h}}_k}[\text{MSE}_k]$ is

$$\overline{\text{MSE}}_k = \sigma_v^2 + \frac{\sigma_n^2}{(N-1)P_p\beta_k}(\sigma_k^2 + \sigma_v^2) + \frac{\sigma_{\text{FC}}^2 (P_p\beta_k + \sigma_n^2)}{\alpha_k^2 (N-1) P_p \beta_k^2} + \sum_{l=1,l\neq k}^{K} \beta_l \left(\frac{P_p\beta_k + \sigma_n^2}{\alpha_k^2 (N-1) P_p \beta_k^2}\right) \alpha_l^2 (\sigma_l^2 + \sigma_v^2). \quad (12)$$

Hence, the optimization problem to design the precoding coefficient α_k for each sensor k such that the EE will be maximized subject to the individual sensor power and MSE constraints can be formulated as given in (24a). Since the optimization problem is in fractional form, which makes it intractable. Hence, one needs to invoke the QT to solve the EE maximization problem as described in the next section.

V. EE MAXIMIZATION USING QUADRATIC TRANSFORM

A QT-based method is proposed to tackle the single-ratio concave-convex fractional problem (CCFP), which decouples the numerator and denominator of the ratio term. This converts a single-ratio CCFP problem into a convex optimization problem. We first state the QT [[11], Corollary 2] in the following proposition.

Proposition 1. *Consider a function-of-ratio problem*

$$\underset{\mathbf{x}}{\textit{maximize}} \quad f\left(\frac{u(\mathbf{x})}{v(\mathbf{x})}\right) \quad \textit{subject to} \quad \mathbf{x} \in \mathcal{X}. \quad (13)$$

where $\mathcal{X}$ is a convex set, and $f(.)$ is a non-negative function. The sequence of functions in the numerator and the denominator are defined such that $u(\mathbf{x}) : \mathbb{R}_n \to \mathbb{R}_+$ and $v(\mathbf{x}) : \mathbb{R}_n \to \mathbb{R}_{++}$ for $1 \leq k \leq K$. Using QT [11], the above problem can be equivalently cast as

$$\underset{\mathbf{x},y}{\text{maximize}} \; f\left(2\sqrt{u(\mathbf{x})}y - y^2 \; v(\mathbf{x})\right)$$
$$\text{subject to} \;\; \mathbf{x} \in \mathcal{X}, \quad y \in \mathbb{R}. \quad (14)$$

where y is an auxiliary variable. Proposition 1 assumes that the functions $u(\mathbf{x})$ and $v(\mathbf{x})$ are non-negative and positive, respectively. We next state another result from [11] which assumes a specific structure on the functions $u(\mathbf{x})$ and $u(\mathbf{x})$.

Proposition 2. *If the function f is non-decreasing and concave, and the ratio* $\frac{u(\mathbf{x})}{v(\mathbf{x})}$ *is in the concave-convex form for the*

$$\overline{\text{SINR}}_k = \frac{\eta_k^2|\alpha_k|^2\sigma_k^2}{V_k|\alpha_k|^2\sigma_k^2 + \delta_k|\alpha_k|^2\sigma_v^2 + \nu_k|\alpha_k|^2(\sigma_k^2+\sigma_v^2) + \sum_{l=1,l\neq k}^{K}(\Gamma_{lk}+\zeta_{lk})|\alpha_l|^2(\sigma_l^2+\sigma_v^2) + \eta_k\sigma_{fc}^2}. \tag{10}$$

$$\mathbf{P1}: \underset{\{\alpha_k\}_{k=1}^K}{\text{maximize}} \ \frac{\sum_{k=1}^{K}\left(\frac{T-\tau}{T}\right)\log_2\left(1+\overline{\text{SINR}}_k\right)}{\left(\frac{T-\tau}{T}\right)\sum_{k=1}^{K}|\alpha_k|^2(\sigma_k^2+\sigma_v^2) + \frac{K\tau}{T}P_p + P_c} \tag{24a}$$

$$\text{subject to} \left(\frac{T-\tau}{T}\right)|\alpha_k|^2(\sigma_k^2+\sigma_v^2) \le P_k,\ 1\le k\le K \tag{24b}$$

$$\sigma_v^2 + \frac{\sigma_n^2}{(N-1)P_p\beta_k}(\sigma_k^2+\sigma_v^2) + \frac{\sigma_{\text{FC}}^2(P_p\beta_k+\sigma_n^2)}{\alpha_k^2(N-1)P_p\beta_k^2} + \sum_{l=1,l\neq k}^{K}\beta_l\left(\frac{P_p\beta_k+\sigma_n^2}{\alpha_k^2(N-1)P_p\beta_k^2}\right)\alpha_l^2(\sigma_l^2+\sigma_v^2) \le \tau_k,\ \forall\, k. \tag{24c}$$

function-of-ratio problem in (13)*, then the problem* (14) *is a concave problem in* $\mathbf{x}$ *and for a given* $\mathbf{x}$*, the optimal value of* y *can be obtained in a closed form as* $y = \frac{\sqrt{u(\mathbf{x})}}{v(\mathbf{x})}$*. The problem* (14) *converges to a stationary point of* (13) *with a non-decreasing objective value after each iteration by a and y being repeatedly optimized.*

We now solve problem (24a) using the QT in Proposition 1. We observe from the objective of (24a) that for EE term the i) numerator is the sum SE of the sensor, which is a non-negative function and; ii) denominator is the total power consumption in the sensor which is a positive function. The numerator and the denominator of the fractional term (EE), using Proposition 1, can therefore be decoupled. The problem (24a) can be recast as

$$\mathbf{P2}: \underset{\{\alpha_k\}_{k=1}^K, y}{\text{maximize}} \ \Big[\sum_{k=1}^{K} 2y\sqrt{\log_2\left(1+\text{SINR}_k\right)} - y^2\left(\left(\frac{T-\tau}{T}\right)\sum_{k=1}^{K}|\alpha_k|^2(\sigma_k^2+\sigma_v^2) + \frac{K\tau}{T}P_p + P_c\right)\Big]$$

subject to $(24a)$ and $(24b)$.

We observe from the objective of $\mathbf{P2}$ that the term $\overline{\text{SINR}}_k$ is in fractional form (see Eq. (10)). By again applying the Proposition 1 to each of SINR_k terms, the problem $\mathbf{P2}$ can be recast as

$$\mathbf{P3}: \underset{\{\alpha_k\}_{k=1}^K, y, \{z_k\}_{k=1}^K}{\text{maximize}} \ \Big[\sum_{k=1}^{K} 2y\sqrt{\log_2\left(1+2z_k\sqrt{\Delta_k} - z_k^2\Lambda_k\right)} - y^2\left(\left(\frac{T-\tau}{T}\right)\sum_{k=1}^{K}|\alpha_k|^2(\sigma_k^2+\sigma_v^2) + \frac{K\tau}{T}P_p + P_c\right)\Big]$$

subject to $(24a)$ and $(24b)$.

where $\Delta_k = \eta_k^2|\alpha_k|^2\sigma_k^2$ and $\Lambda_k = V_k|\alpha_k|^2\sigma_k^2 + \sum_{l=1,l\neq k}^{K}\Gamma_{lk}|\alpha_l|^2\sigma_l^2 + \sum_{l=1}^{K}\frac{\beta_l\sigma_n^2}{P_p\beta_l+\sigma_n^2}\eta_k|\alpha_l|^2\sigma_l^2 + \sum_{l=1}^{K}\left(\Gamma_{lk} + \frac{\eta_k\beta_l\sigma_n^2}{P_p\beta_l+\sigma_n^2}\right)|\alpha_l|^2\sigma_v^2 + \eta_k\sigma_{fc}^2$ are defined as By inspection, both the quantities Δ_k and Λ_k are convex in nature. While we want Δ_k to be concave and hence we derive its linear approximation using first order Taylor series expansion as shown below:

$$\Delta_k = \eta_k^2|\alpha_k|^2\sigma_k^2 \approx \eta_k^2 a_k^2\sigma_k^2 + 2\eta_k^2\sigma_k^2\alpha_k^*\left(\alpha_k - a_k\right) = \Delta_k^{'}.$$

where a_k is the initial value of the precoding coefficient α_k. Hence, the final optimization problem can be formulated as

$$\mathbf{P4}: \underset{\{\alpha_k\}_{k=1}^K, y, \{z_k\}_{k=1}^K}{\text{maximize}} \ \Big[\sum_{k=1}^{K} 2y\sqrt{\log_2\left(1+2z_k\sqrt{\Delta_k^{'}} - z_k^2\Lambda_k\right)} - y^2\left(\left(\frac{T-\tau}{T}\right)\sum_{k=1}^{K}|\alpha_k|^2(\sigma_k^2+\sigma_v^2) + \frac{K\tau}{T}P_p + P_c\right)\Big]$$

subject to $(24a)$ and $(24b)$.

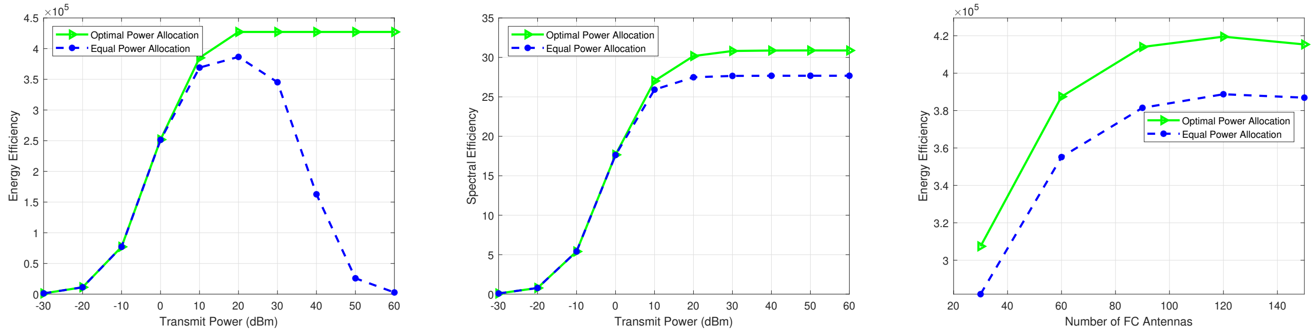
The above optimization is now convex in nature and can be solved efficiently using the CVX [12]. Algorithm 1 summarizes the proposed scheme.

Algorithm 1 EE maximization using QT

Input: ϵ (Threshold), l_{max} (Maximum QT iterations)
Output: $\{\alpha_k\}_{k=1}^K$
1: set $\alpha_k^{(0)} = \frac{P_k}{(\sigma_v^2+\sigma_k^2)}$, $1\le k\le K$ and $\boldsymbol{\alpha}$ with equal power allocation
2: for $t=1$ to l_{max}
3: Given feasible $\{\alpha_k\}_{k=1}^K$, compute $z_k = \frac{\sqrt{\Delta_k}}{\Lambda_k}$, $1\le k\le K$ and $y = \frac{\sqrt{u(\mathbf{x})}}{v(\mathbf{x})}$.
4: Compute $\{\alpha_k\}_{k=1}^K$ by solving P4
5: Repeat until convergence $||\boldsymbol{\alpha}^{(l+1)} - \boldsymbol{\alpha}^{(l)}|| \ge \epsilon$ or $l \le l_{\text{max}}$
6: end
7: **return** $\{\alpha_k\}_{k=1}^K$.

VI. Simulation Results

In this section, we present results from the numerical experiments to demonstrate the performance of the proposed scheme by performing Monte Carlo iterations. We assume that the sensors are distributed randomly in a circular area of radius 400 meters with FC at the center and each sensor is distributed randomly at least $d_{min} = 75$ meter distance from the FC. The large scale fading coefficients follow the path loss model as



(a) (b) (c)

Fig. 2: (a) EE and (b) SE performance comparison between the proposed scheme and EPA versus the transmit power. (c) EE versus the number for antennas at the FC

$\Upsilon - 10a \log_{10}\left(\frac{d_k}{1km}\right) + F_k$, where Υ represent the channel gain at the reference distance of 1 km, d_k is the separation distance between the sensor k and the FC, a is the path-loss exponent which determines the rate at which the signal decays with the distance and $F_k \sim \mathcal{CN}\left(0, \sigma_f^2\right)$ is the shadow fading term that creates log-normal random variations around the transmit and receive antennas of each sensor k. We consider $K = 10$ sensors, and $N = 64$ antennas at the FC unless otherwise stated. The observation and FC noise variances are defined as $\sigma_o^2 = 0.01$ and $\sigma_{fc} = \frac{1}{\text{SNR}_{fc}}$, respectively.

Fig. 2 (a) depicts the EE performance as a function of the transmit power of the sensors in the IoT network. From a performance comparison point of view, we have plotted the performance of equal power allocation (EPA), where the total available transmit power is distributed equally among the sensors in the network. It can be observed from the figure that at low transmit power, both schemes perform similarly, which makes it intuitive that at low transmit power levels, it does not make any difference whether we distribute power equally or optimally. But as transmit power increases, the proposed optimal power allocation scheme outperforms the EPA scheme. Most importantly, once the optimal EE is obtained, it remains constant, while the EPA-based scheme is not able to make use of the extra transmit power and decreases after attaining the maximum EE.

Fig. 2 (b) plots the SE as a function of transmit power at each sensor. It can once again be seen that the proposed optimal power allocation-based scheme outperforms EPA by a significant margin, which shows the efficacy of the proposed scheme. Fig. 2 (c) shows the EE as a function of the number of receive antennas (N) at the FC. As the number of antennas increases in the IoT network, the EE performance improves, and the proposed scheme once again performs better than the EPA, once again reinstating the fact that the proposed design is superior.

VII. Conclusion

This paper examined the problem of EE maximization while satisfying the desired level of MSE performance and following the transmit power constraint. The MMSE-based imperfect channel is used to combine the received signal at the FC, which makes the proposed design easier to implement in practice. QT and first-order Taylor series approximations are used to solve the intractable CCFP EE maximization problem. The proposed approach reduces the channel estimation overhead, and hence, the proposed algorithm suits well for battery-operated tiny sensor-based IoT networks. Simulation results have demonstrated the performance of the proposed design.

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