Environment-Aware Joint Active/Passive Beamforming for RIS-Aided Communications Leveraging Channel Knowledge Map

Ehsan Moeen Taghavi, *Graduate Student Member, IEEE*, Ramin Hashemi, *Graduate Student Member, IEEE*, Nandana Rajatheva, *Senior Member, IEEE*, and Matti Latva-Aho, *Senior Member, IEEE*

***Abstract*— Reconfigurable intelligent surface (RIS)-aided communication is a promising technology for 6G systems to reconfigure the propagation environment proactively. However, it requires efficient real-time channel training, which suffers excessive overhead. To resolve this challenge, taking advantage of sensing with radio waves and localization, we propose a novel environment-aware joint active/passive beamforming for RIS-aided wireless communication based on the new concept of channel knowledge map (CKM). In the proposed scheme, the user equipments (UEs) location information is combined with the radio environment information provided by CKM to achieve efficient beamforming without real-time training. Simulation results show the proposed scheme's superior performance over training-based beamforming, which is also quite robust to errors related to UE's location in practice.**

***Index Terms*— Channel knowledge map, energy efficiency, reconfigurable intelligent surface.**

I. Introduction

BY RECONFIGURING the wireless propagation environment in 6G communications systems, RIS offer spectrum and energy efficient wireless communication cost effectively. However, channel estimation is the major challenge in realizing the advantages of RIS-aided communications due to the passive elements in the RIS and the prohibitive overhead caused by massive elements. Hence, obtaining the required channel state information (CSI) for beamforming becomes intractable [1].

Extensive research for proposing efficient RIS channel estimation schemes has been devoted. Methods for estimating the cascaded channels between UEs and base station (BS) through the RIS were proposed in [2], [3], [4], and [5]. The authors in [3] provided the cascaded channel by turning on only one RIS passive element at each time and successively estimating the channel with each RIS passive element. However, the accuracy of the estimated CSI is so vulnerable to noise due to the week training signal estimated by one element turned on. Also, a subgroup-based channel estimation was proposed in [4] for RIS-aided communications. The authors in [5] considered the properties of channel correlation among the UEs based on the common BS-RIS link to propose a multi-user channel estimation scheme. Furthermore, the cascaded channel estimation based on compress sensing techniques, considering BS-RIS channel sparsity properties, was investigated in [6], [7], and [8]. Searching for the optimal passive beamforming given a predefined codebook is another practical approach instead of CSI estimation [9]. However, this approach increases the beam training overhead to ensure high resolution. The above techniques disregard the UE's location and the actual communication environment. Recent advances in localization and sensing technologies have increased interest in utilizing location information and geolocation-based databases for wireless communication systems. One such concept is a CKM which provides location-specific information regarding intrinsic radio channels with no need for sophisticated real-time CSI acquisitions [10]. Additionally, [11] analyses the key features involved in the construction and utilization of CKM.

This letter proposes a new approach for joint optimized active/passive beamforming in RIS-aided communications, enabling environment-aware communication through the use of CKM which does not require any real-time channel training. CKM is a site-specific database that involves the transceivers' locations and channel-related information useful to enhance environmental awareness and facilitate real-time CSI acquisition. Due to the drastic increase in channel dimensions and training overhead, CKM plays a vital role in 6G networks that aim to achieve extremely high capacity, low latency, and ultra-massive connectivity. With the proposed training-free beamforming, the most appropriate and optimized active and passive beams are designed with both the location and the environmental information provided by the CKM. The simulation results show that the proposed environment-aware beamforming scheme significantly outperforms the training-based baseline and the proposed method is robust to uncertainties associated with the location of UEs in practice.

II. System Model

Consider a downlink RIS-aided mmWave cell, where a multi-antenna BS serves K single-antenna UEs with the help of the RIS as shown in Fig. 1. We assume the BS has $M \gg 1$ antennas, and the RIS is equipped with $N \gg 1$ passive elements. Besides, there is no direct link between the BS and the UEs due to severe blockage in the mmWave communications. Let us denote $\boldsymbol{f}_k \in C^M$ as the active transmit beamforming vector for each UE k. Also, $\boldsymbol{\theta} = [\theta_1, \theta_2, \dots, \theta_N]^T$ as the passive beamforming vector, i.e., the reflection coefficients applied on the incident signal at the RIS. Our aim is to design an optimized environment-aware active/passive beamforming $(\boldsymbol{f}, \boldsymbol{\theta}) \in \mathcal{H}$. The transmitted signal from BS is $\boldsymbol{x} = \sum_{k\in\mathcal{K}} \boldsymbol{f}_k s_k$ where s_k is the symbol data for UE k distributed as a zero mean and unit variance

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The authors are with the Centre for Wireless Communications, University of Oulu, 90014 Oulu, Finland (e-mail: seyed.moeentaghavi@oulu.fi; ramin.hashemi@oulu.fi; nandana.rajatheva@oulu.fi; matti.latva-aho@oulu.fi).

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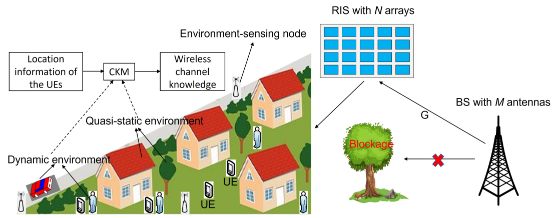

Fig. 1. Environment awareness is enabled by CKM through a location-tagged database of channel-related information, providing channel knowledge.

i.i.d. random variable and $E\left[\boldsymbol{x}^{*}\boldsymbol{x}\right]=\sum_{k\in\mathcal{K}}Tr\left(\boldsymbol{f}_{k}\boldsymbol{f}_{k}^{*}\right)\leq P$ where P is the maximum transmit power of the BS. Therefore, the received signal at UE k will be $y_k = \boldsymbol{h}_{r_k}^{*}\boldsymbol{\Theta}^{*}\boldsymbol{G}^{*}\boldsymbol{x}+z_k$ and the corresponding signal-to-interference-plus-noise ratio (SINR) at UE k is given by

$$\mathrm{SINR}_k(\mathcal{H}) \triangleq \frac{|\boldsymbol{h}_k^{*}\boldsymbol{f}_k|^2}{\sum_{j\in\mathcal{K}, j\neq k}|\boldsymbol{h}_k^{*}\boldsymbol{f}_j|^2+\sigma^2}. \tag{1}$$

where $z_k \sim CN(0,\sigma^2)$ is the receiver noise. It is noteworthy that $\boldsymbol{h}_k = \boldsymbol{G\Theta h}_{r_k}$, $\boldsymbol{h}_{r_k} \in C^N$ is denoted as the reflected link between RIS and UE k, $\boldsymbol{G} \in C^{M\times N}$ relates to BS-RIS link, and $\boldsymbol{\Theta} = \mathrm{diag}(\theta_1, \theta_2, \ldots, \theta_N)$ as the diagonal phase-shift matrix. Based on the assumption of perfect CSI availability, the maximum energy efficiency (EE) is written by

$$U_{eff}(\mathcal{H}^{*}) = \frac{\sum_{k\in\mathcal{K}}\ln(1+\mathrm{SINR}_k(\mathcal{H}^{*}))}{U_{TP}(\mathcal{H}^{*})}, \tag{2}$$

where $(\boldsymbol{f^{*}}, \boldsymbol{\theta^{*}}) \in \mathcal{H}^{*}$ are the optimal active and passive beams. In this case, $U_{TP}(\mathcal{H}) = \sum_{k\in\mathcal{K}}\|\boldsymbol{f}_k\|^2 + P_{Cir}$ represents the total power consumed by the system. Furthermore, P_{Cir} represents the constant circuit power dissipation, including the power consumption of the BS, RIS, and all UEs.

However, achieving the maximum EE in practice is problematic because it requires perfect CSI, which is very difficult for RIS-aided communication. In spite of the fact that several channel estimation approaches have been proposed, they often result in high training overheads that increase as the number of RIS elements increases $(N \gg 1)$. Considering S_{tr} as the number of symbol duration used for channel training $(S_{tr} \leq S)$, based on the assumption that the cascaded channel matrices h_k have $M \times N$ unknown entries; hence, $S_{tr} \geq MN \gg 1$ is generally required for channel training. As a result, a channel training-based beamforming can effectively achieve an average network spectral efficiency (SE) of [12]

$$\begin{aligned} SE_{tr} &= \frac{S-S_{tr}}{S}\sum_{k\in\mathcal{K}}\ln(1+\mathrm{SINR}_k(\mathcal{H}^{*})) \\ &\leq \frac{S-(M\times N)}{S}\sum_{k\in\mathcal{K}}\ln(1+\mathrm{SINR}_k(\mathcal{H}^{*})), \end{aligned} \tag{3}$$

Taking into account channel training overhead as factor $\frac{S-S_{tr}}{S}$, a result of (3) indicates that for RIS-aided communication when $M\times N$ is comparable or exceeds channel coherent duration S, which is expected since M and N are typically quite large, a significant gap exists between practically achievable SE and maximum possible SE assuming perfect CSI.

On the basis of CKM, we propose a new approach to RIS-aided communication, which integrates active and passive beamforming to address the above issues. It is possible to design optimal active beamformers as well as passive beamformers based on the location of the UE, without requiring any real-time channel training (i.e., training-free beamforming). As a result of exploiting UEs' readily available location information in today's wireless networks with increasingly accurate location information, environment-aware wireless communication enabled by CKM has high practical appeal.

III. Environment-Aware Optimal Beamforming

A. Environment-Aware Communications Enabled by CKM

Typically, wireless channels are determined by several factors, including the radio wave property (such as wavelength), the transceivers' locations, as well as the actual environment of radio propagation. In recent decades, there have been extensive attempts to characterize wireless channels using stochastic or geometric methods mathematically. In reality, however, the models that are proposed to model the channel utilize partial information about the transceivers' locations, such as distances between the transmitter and receiver, rather than precise locations, as well as very coarse information about the environment (such as urban, suburban, or rural areas, rather than the actual environment in which the communication occurs). While the channel models developed using these approaches are tractable and easy to generalize, when they are applied to actual communication scenarios, the modeled channels are inevitably subject to non-negligible errors. So, it is necessary to perform real-time channel estimations using pilot-based channel training. Conversely, environment-aware wireless communication is expected to substantially reduce training overhead in large-dimension MIMO systems due to the continuous advancements in localization technologies and improved environmental awareness of UEs [10].

With no need for traditional channel training, the important features of the wireless channels can be attained with CKM. Also, by advancing localization and environmental awareness, there is a possibility of resolving the issue of prohibitive training overhead for large dimension MIMO systems [12]. By utilizing a CKM database, which contains channel-related information and is tagged with the transceivers' locations, enabling environmental awareness, as illustrated in Fig. 1, channel knowledge is provided [13]. The equivalent cascaded channel $(\boldsymbol{h}_k)$ of a RIS-aided communication system is primarily affected by the location of the UEs $(\mathcal{Q}_k)$ and the environment in which it is propagated $(\mathcal{E}_k)$ such as $\boldsymbol{h}_k = \mathcal{G}_1(\mathcal{Q}_k, \mathcal{E}_k)$. In practice, it is challenging to characterize $\mathcal{G}_1$ precisely because it is an unknown function. It is fortunate that a novel approach to tackle this intractable problem is the use of CKM, which aims to map any possible UE location and its channel knowledge specific to that location. Compared to the UE locations, the wireless propagation environment (such as the locations, heights, and dielectric properties of surrounding objects) changes on a much larger time scale. It is notable that the impact of those environmental factors that may vary with comparable time scale as UE locations (such as pedestrians) on the wireless channel is much less than UE locations in practice. Therefore, the CKM needs to be updated only when there is a significant environmental change (which can be detected by environment-sensing nodes as illustrated in Fig. 1) that happens at a much larger time scale than the channel coherence time. Hence, having known the UE locations with high accuracy (provided via GPS and other innovative technologies for localization), the wireless channel gain can be approximately provided with the CKM without any channel training needed as $\boldsymbol{h}_k \approx \mathcal{G}_2(\mathcal{Q}_k)$. Note that the key techniques to build CKM were investigated in [11] and [14]. The CKM is a training-free approach that does not require channel estimation. Instead, the CKM can be obtained by using an environment sensing technique to extract environmental features, such as the location and type of obstacles and reflecting surfaces, and then mapping these features to the wireless propagation characteristics in the environment. The CKM can be stored in a database and updated only when there is a significant change in the environment, which can be detected by using environment sensing nodes. Regarding the complexity of obtaining the CKM, it mainly depends on the complexity of the environment sensing technique used and the frequency of updating the CKM. However, once the CKM is obtained and stored, the complexity of using it for environment-aware communications is low, as the wireless propagation characteristics in the environment can be easily retrieved from the CKM. Nonetheless, directly obtaining the MIMO channel coefficients requires a substantial amount of computing and storage resources. As a solution to this problem, we propose the following approach based on the concept of CKM to obtain optimal beamforming.

B. Environment-Aware Active/Passive Beamforming

As discussed in the previous subsection, the channel information in contemporary wireless systems is attainable based on CKM. To provide optimal active/passive beamforming in RIS-aided communications with no challenge in computing and storage of CKM, the coverage area of the BS is divided into several sections such that the large-scale parameters in each section do not vary significantly. Hence, the wireless channel gain in each section can be assumed to be a specific value (regardless of path loss which can be determined precisely) provided by CKM. In the proposed scenario, only the wireless channel information of the sections is stored and calculated in CKM, which is significantly less than the wireless channel information of all possible locations in the cell. Therefore, based on CKM and UEs' location, the wireless channel gain of UEs ($\boldsymbol{h}_k$) can be attained considering the path loss attenuation and the sections where the UEs are located. Hence, by assigning the provided wireless channel gain of the sections to the wireless channel gain of UEs ($\boldsymbol{h}_k$), EE will be maximized by designing passive beamforming at RIS and active beamforming at BS as follows

$$\max_{\mathcal{H}} \; U_{eff}(\mathcal{H}) \text{ s.t. C1: } \sum_{k\in\mathcal{K}} \|\boldsymbol{f}_k\|^2 \leq P, \;\; \text{C2: } |\theta_n|^2 \leq 1, \forall n \in \mathcal{N}$$

In order to deal with the logarithm in the objective function, the Lagrangian Dual Transform (LDT) is applied [15]. Therefore, the problem can be expressed as follows

$$\max_{\mathcal{H},\boldsymbol{\pi}} \; \frac{\sum_{k=1}^{K}(\ln(1+\pi_k) - \pi_k + \frac{(1+\pi_k)\text{SINR}_k}{1+\text{SINR}_k})}{\sum_{k\in\mathcal{K}} ||\boldsymbol{f}_k||^2 + P_{Cir}}, \quad \text{s.t. C1, C2.}$$

where $\boldsymbol{\pi} = [\pi_1, \pi_2, \ldots, \pi_K]$, and π_k is auxiliary variable for decoding SINR_k. For given $\mathcal{H}$, the optimal value of π_k can be found as $\pi_k^{\text{opt}} = \text{SINR}_k$. Thus, by substituting π_k^{opt} in the utility function, the optimization problem (OP) is reduced to

$$\max_{\mathcal{H}} \; \frac{\sum_{k=1}^{K} \frac{\tilde{\pi}_k \text{SINR}_k}{1+\text{SINR}_k}}{\sum_{k\in\mathcal{K}} \|\boldsymbol{f}_k\|^2 + P_{Cir}}, \quad \text{s.t. C1, C2.} \tag{4}$$

where $\tilde{\pi}_k = (1+\pi_k)$. (4) is the multiple-ratio FP summation, and fractional programming techniques can solve the non-convexity of the problem due to the ratio operation [15]. The following two subsections provide further details on how to solve $\boldsymbol{f}$ by fixing $\boldsymbol{\Theta}$, and to solve $\boldsymbol{\Theta}$ by fixing $\boldsymbol{f}$, respectively.

1) Active BS Beamforming: Given fixed $\boldsymbol{\Theta}$ in (4), the sub-problem for active beamforming matrix $\boldsymbol{f}$ will be

$$\max_{\boldsymbol{f}} \; \frac{\sum_{k=1}^{K} \left(\frac{\tilde{\pi}_k |\boldsymbol{h}_k^* \boldsymbol{f}_k|^2}{\sum_{j\in\mathcal{K}} |\boldsymbol{h}_k^* \boldsymbol{f}_j|^2 + \sigma^2} \right)}{\sum_{k\in\mathcal{K}} \|\boldsymbol{f}_k\|^2 + P_{Cir}}, \quad \text{s.t. C1.} \tag{5}$$

Using quadratic transform to represent the numerator in (5), we get the following problem

$$\begin{aligned} \textbf{P1}: \max_{\boldsymbol{f},\boldsymbol{\beta}} \quad & U_{eff2}(\boldsymbol{f},\boldsymbol{\beta}) \\ \triangleq \; & \frac{\sum_{k=1}^{K} \left(2\sqrt{\tilde{\pi}_k}\Re(\beta_k^* \boldsymbol{h}_k^* \boldsymbol{f}_k) - |\beta_k|^2 \left(\sum_{j\in\mathcal{K}} |\boldsymbol{h}_k^* \boldsymbol{f}_j|^2 + \sigma^2 \right) \right)}{\sum_{k\in\mathcal{K}} ||\boldsymbol{f}_k||^2 + P_{Cir}}, \\ \text{s.t.} \quad & \text{C1.} \end{aligned} \tag{6}$$

where $\boldsymbol{\beta} = \{\beta_k | \forall k\}$ are auxiliary variables. (6) is a biconvex OP. To solve it, one method is to fix one of $\boldsymbol{f}$ and $\boldsymbol{\beta}$, then to solve the convex OP corresponding to the other [16]. The optimal $\boldsymbol{\beta}$ given $\boldsymbol{f}$ is obtained by setting $\frac{\partial U_{eff2}(\boldsymbol{f},\boldsymbol{\beta})}{\partial \beta} = 0$ as

$$\beta_k^{opt} = \frac{\sqrt{\tilde{\pi}_k} \boldsymbol{h}_k^* \boldsymbol{f}_k}{\sum_{j\in\mathcal{K}} |\boldsymbol{h}_k^* \boldsymbol{f}_j|^2 + \sigma^2}. \tag{7}$$

Then, fixing $\boldsymbol{\beta}$, and considering $\boldsymbol{\Delta} \triangleq \sum_{j\in\mathcal{K}} |\beta_j|^2 \boldsymbol{h}_j \boldsymbol{h}_j^*$, $\boldsymbol{\Gamma}_k \triangleq \sqrt{\tilde{\pi}_k} \beta_k^* \boldsymbol{h}_k$, $U_{eff2}(\boldsymbol{f},\boldsymbol{\beta})$ can be represented as a fraction of the concave function over the convex function

$$U_{eff2}(\boldsymbol{f}) = \frac{\sum_{k\in\mathcal{K}} (-\boldsymbol{f}_k^* \boldsymbol{\Delta} \boldsymbol{f}_k + 2\Re(\boldsymbol{f}_k^* \boldsymbol{\Gamma}_k))}{\sum_{k\in\mathcal{K}} ||\boldsymbol{f}_k||^2 + P_{Cir}}. \tag{8}$$

The solution to single-ratio concave-convex fractional problems can be achieved by applying fractional programming techniques such as Generalized Dinkelbach's algorithm. Hence, a global bound maximization for (8) can be expressed as the following convex problem leads to the optimal $\boldsymbol{f}$

$$\begin{aligned} \textbf{P1.1}^{(i)}: \max_{\boldsymbol{f}} \quad & U_{eff3}(\boldsymbol{f}^{(i)}) \\ \triangleq \; & \sum_{k\in\mathcal{K}} (-\boldsymbol{f}_k^* \boldsymbol{\Delta} \boldsymbol{f}_k + 2\Re(\boldsymbol{f}_k^* \boldsymbol{\Gamma}_k)) - y^{(i)} \Big(\sum_{k\in\mathcal{K}} \|\boldsymbol{f}_k\|^2 + P_{Cir} \Big), \\ \text{s.t.} \quad & \text{C1.} \end{aligned} \tag{9}$$

where y is a new auxiliary variable, which is iteratively updated with the iteration index (i) as

$$y^{(i+1)} = \frac{\sum_{k\in\mathcal{K}} \left(-\boldsymbol{f}_k^{(i)^*} \boldsymbol{\Delta} \boldsymbol{f}_k^{(i)} + 2\Re(\boldsymbol{f}_k^{(i)^*} \boldsymbol{\Gamma}_k) \right)}{\sum_{k\in\mathcal{K}} \|\boldsymbol{f}_k^{(i)}\|^2 + P_{Cir}}, \tag{10}$$

As y is non-decreasing with each iteration of the algorithm, convergence can be proved by updating y in accordance with (10) and solving for $\boldsymbol{f}$ in (9). The iterative algorithm actually converges to the global optimum solution of (8) when the single-ratio problem (8) is a concave-convex fractional programming. To reach the optimal $\boldsymbol{f}$, first, initialize $y^{(0)}$ from a feasible point $\boldsymbol{f}^{(0)}$ of the problem (6), after that, the OP in (9) is solved iteratively to generate a sequence $\{\boldsymbol{f}^{(i)}\}, i = 1, 2, \ldots$ of feasible and improved points toward the optimal solution of (6). It is also notable that at iteration (i), $\boldsymbol{f}^{(i-1)}$ is used as a feasible point for solving (9) and obtaining $\boldsymbol{f}^{(i)}$. Also, note that CVX easily solves the OP in (9) as a convex quadratically constrained quadratic program (QCQP). In order to achieve convergence, a series of convex problems (9) must be solved and repeated. For a given error tolerance $\xi > 0$, with the initial feasible point $\boldsymbol{f}^{(0)}$, the solution for problem (5) is achieved when $|U_{eff3}(\boldsymbol{f}^{(i)}) - U_{eff3}(\boldsymbol{f}^{(i-1)})| \leq \xi$.

2) Passive RIS Beamforming: Similarly, given fixed $\boldsymbol{f}$ and by denoting $\boldsymbol{h}_k = \boldsymbol{G\Theta h}_{r_k}$, the utility function in (4) is

$$\max_{\boldsymbol{\Theta}} \quad \frac{\sum_{k=1}^{K}\left(\frac{\tilde{\pi}_k|(\boldsymbol{h}_{r_k}^{*}\boldsymbol{\Theta}^{*}\boldsymbol{G}^{*})\boldsymbol{f}_k|^2}{\sum_{j\in\mathcal{K}}|(\boldsymbol{h}_{r_k}^{*}\boldsymbol{\Theta}^{*}\boldsymbol{G}^{*})\boldsymbol{f}_j|^2+\sigma^2}\right)}{\sum_{k\in\mathcal{K}}\|\boldsymbol{f}_k\|^2+P_{Cir}}, \quad \text{s.t.} \quad \text{C2}. \quad (11)$$

By defining $\boldsymbol{l}_{j,k} \triangleq diag(\boldsymbol{h}_{r_k}^{*})\boldsymbol{G}^{*}\boldsymbol{f}_j, \boldsymbol{l}_{j,k} \in C^N$, and $|(\boldsymbol{h}_{r_k}^{*}\boldsymbol{\Theta}^{*}\boldsymbol{G}^{*})\boldsymbol{f}_j|^2 = |\boldsymbol{\theta}^{*}diag(\boldsymbol{h}_{r_k}^{*})\boldsymbol{G}^{*}\boldsymbol{f}_j|^2 = |\boldsymbol{\theta}^{*}\boldsymbol{l}_{j,k}|^2$, the utility function in (11) is equivalently reformulated as

$$U_{eff4}(\boldsymbol{\theta}) \triangleq \frac{\sum_{k=1}^{K}\left(\frac{\tilde{\pi}_k|\boldsymbol{\theta}^{*}\boldsymbol{l}_{k,k}|^2}{\sum_{j\in\mathcal{K}}|\boldsymbol{\theta}^{*}\boldsymbol{l}_{j,k}|^2+\sigma^2}\right)}{\sum_{k\in\mathcal{K}}\|\boldsymbol{f}_k\|^2+P_{Cir}}. \quad (12)$$

Since the numerator in the fraction $U_{eff4}(\boldsymbol{\theta})$ is fractional programming, on the basis of the quadratic transform, it can be expressed as follows [15]

$$U_{eff5}(\boldsymbol{\theta},\boldsymbol{\epsilon}) \triangleq \sum_{k=1}^{K}\left(2\sqrt{\tilde{\pi}_k}\Re(\epsilon_k^{*}\boldsymbol{\theta}^{*}\boldsymbol{l}_{k,k}) - |\epsilon_k|^2\Big(\sum_{j\in\mathcal{K}}|\boldsymbol{\theta}^{*}\boldsymbol{l}_{j,k}|^2+\sigma^2\Big)\right), \quad (13)$$

where $\boldsymbol{\epsilon} = \{\epsilon_k|\forall k\}$ are auxiliary variables. The OP is therefore reformulated as

$$\textbf{P2}: \max_{\boldsymbol{\theta},\boldsymbol{\epsilon}} \quad U_{eff5}(\boldsymbol{\theta},\boldsymbol{\epsilon}) \quad \text{s.t.} \quad \text{C2}, \quad (14)$$

For a given $\boldsymbol{\theta}$, the optimal $\boldsymbol{\epsilon}$ can be analytically expressed as

$$\epsilon_k^{opt} = \frac{\sqrt{\tilde{\pi}_k}\boldsymbol{\theta}^{*}\boldsymbol{l}_{k,k}}{\sum_{j\in\mathcal{K}}|\boldsymbol{\theta}^{*}\boldsymbol{l}_{j,k}|^2+\sigma^2}. \quad (15)$$

Given optimal $\boldsymbol{\epsilon}^{\text{opt}}$, the OP for $\boldsymbol{\theta}$ is expressed as

$$\max_{\boldsymbol{\theta}} \quad -\boldsymbol{\theta}^{*}\boldsymbol{B\theta} + 2\Re(\boldsymbol{\theta}^{*}\boldsymbol{N}) \quad \text{s.t. C2}, \quad (16)$$

where $\Re(\cdot)$ represents the real part of a complex number and

$$\boldsymbol{B} \triangleq \sum_{k\in\mathcal{K}}|\epsilon_k|^2\sum_{j\in\mathcal{K}}\boldsymbol{l}_{j,k}\boldsymbol{l}_{j,k}^{*}, \quad \boldsymbol{N} \triangleq \sum_{k\in\mathcal{K}}\sqrt{\tilde{\pi}_k}\epsilon_k^{*}\boldsymbol{l}_{k,k}. \quad (17)$$

Since $\boldsymbol{l}_{k,j}\boldsymbol{l}_{k,j}^{*}$ for all k, j are positive definite matrice, $\boldsymbol{B}$ is a positive definite matrix. Also, the utility function in (16) is a quadratic concave function of $\boldsymbol{\theta}$. As a result, the problem can only be characterized as QCQP, and its non-convexity can only be attributed to the constraints. As an alternative to non-convex

Algorithm 1 Environment-Aware Active/Passive Beamforming Algorithm

Input: Location information of the UEs, the environment information offered by CKM;
Output: Environment-aware active/passive beamformers
Attaining the channel gain of UEs ($\boldsymbol{h}_k$) based on CKM;
Set $\hat{i} \leftarrow 0$ and initialize $\boldsymbol{f}, \boldsymbol{\theta}$;
while *convergence not met and* $\hat{i} < I_{out}$ **do**
  Set $\hat{i} \leftarrow \hat{i}+1, i \leftarrow 0$;
  Compute $\boldsymbol{\pi}$ from $\pi_k^{\text{opt}} = \text{SINR}_k$;
  Compute $\boldsymbol{\beta}$ from (7);
  Initialize $y^{(0)}$;
  while *convergence not met and* $i < I_{in}$ **do**
    Set $i \leftarrow i+1$;
    Solve convex program $\textbf{P1.1}^{(i)}$ from (9) to find optimal solution $\boldsymbol{f}^{(i)}$, using $\boldsymbol{\pi}, \boldsymbol{\beta}, y^{(i)}$;
    Compute $y^{(i+1)}$ from (10), using $\boldsymbol{f}^{(i)}, \boldsymbol{\beta}, \boldsymbol{\pi}$;
  Compute $\boldsymbol{\epsilon}$ from (15);
  Solve convex program $\textbf{P2.1}^{(\hat{i})}$ to find $\boldsymbol{\theta}$;

constraints, the following convex quadratic constraints can be substituted as $\boldsymbol{\theta}^{*}\boldsymbol{e}_n\boldsymbol{e}_n^{*}\boldsymbol{\theta} \leq 1$ for $\forall n \in \mathcal{N}$ where $\boldsymbol{e}_n \in \mathcal{R}^N$ represents an elementary vector involving a one at the n^{th} position. As a result, the convex QCQP is formulated as

$$\textbf{P2.1}^{(\hat{i})}: \max_{\boldsymbol{\theta}} -\boldsymbol{\theta}^{*}\boldsymbol{B\theta}+2\Re(\boldsymbol{\theta}^{*}\boldsymbol{N}) \text{ s.t. } \boldsymbol{\theta}^{*}\boldsymbol{e}_n\boldsymbol{e}_n^{*}\boldsymbol{\theta}\leq 1, \forall n\in\mathcal{N},$$

which is solved by CVX [17]. A summary of our proposed environment-aware active/passive beamforming is provided in Algorithm 1. In the proposed algorithm, two QCQP problems are solved using CVX at each iteration. The size of the problem is determined by the number of variables M, and N, respectively. At both sub-problems, the constraints are quadratic, and the objective function is also quadratic, which means that the problem is convex and can be solved efficiently using a suitable convex optimization solver. The complexity of solving a convex OP using an interior-point method such as those used by Gurobi, MOSEK, or SeDuMi is typically polynomial in the size of the problem. In particular, the complexity of interior-point methods is usually proportional to M^3, and N^3, respectively. The complexity of Algorithm 1 can be estimated by considering the number of variables in each of the two QCQP sub-problems. The complexity of solving each QCQP sub-problem using CVX is proportional to the cube of the number of variables, which gives a complexity of M^3 for sub-problem **P1.1** and N^3 for sub-problem **P2.1**. Therefore, the overall complexity of Algorithm 1 can be estimated as $M^3 + N^3$.

IV. Simulation Results

Based on the concept of CKM and knowing the UEs' locations, the active beamformers at the BS and passive beamformers at the RIS are optimized to achieve maximum network EE. An actual physical environment is considered while fixing the BS and RIS locations. Also, the UEs are randomly distributed in a $50m \times 50m$ square area. BS and RIS are placed in such a way that a LoS path exists between them, but the links between BS and UEs are blocked. In addition

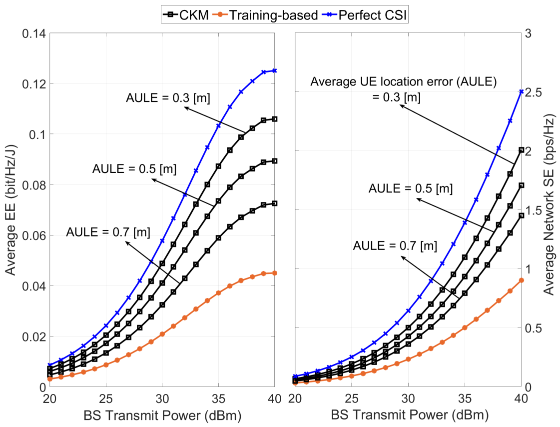

Fig. 2. Average network SE and EE for perfect CSI, CKM based on estimating the UEs' locations with error, and training-based beamforming.

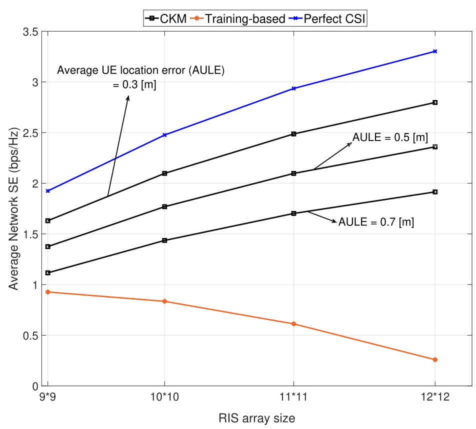

Fig. 3. Average network SE versus the number of RIS elements.

to these blockers, other obstructions may be located randomly within the square area, which may affect the LoS link for the RIS-UEs channels. There are 8×8 uniform planar array (UPA) antennas installed at the BS. Besides, the RIS is composed of 10×10 reflecting passive elements. At the carrier frequency of $73GHz$, and the system bandwidth of $300MHz$, the power spectral density of the noise is $-174dBm/Hz$. Also, the transmit power P at the BS varies from $20dBm$ to $40dBm$. It is assumed that the channel coherent time spans over for $S = 10^4$ symbols, and the simulations presented below are the result of averaging over 10^4 iterations.

Figure 2 shows the average network SE and EE for perfect CSI, CKM based on estimating the UEs' locations with error, and channel training-based, respectively. By comparing the curves, it is observed that although the error in estimating the locations degrades the rate performance logarithmically, it still outperforms the channel training-based scheme that affects the communication rate linearly. Hence, the proposed environment-aware beamforming demonstrates its robustness to UE location errors in practice.

Considering the training overhead, the average network SE is depicted in Fig. 3. The results indicate that the training-based SE experiences a significant decrease as the number of RIS arrays increases. This is because the training overhead surpasses the resulting gain for RIS elements in passive beamforming. In contrast, the proposed CKM schemes consistently improve as N increases. As the number of reflective arrays grows, more signals can be reflected, which results in enhanced passive beamforming.

V. Conclusion

We investigated environment-aware active/passive beamforming for RIS-aided communication enabled by CKM, which requires no online training and reduces the overhead for mmWave systems while achieving high energy-efficient performance. According to simulation results, CKM can significantly improve active/passive beamforming compared to training-based beamforming and is quite robust to errors associated with the location of UEs in practice.

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