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Positioning Information-Based Codebook for Reconfigurable Intelligent Surface Passive Beamforming

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ABSTRACT In this paper, we design a positioning information (PI) based codebook (PI-CB) for reconfigurable intelligent surface (RIS) passive beamforming (PBF), in online stage. In which, corresponding to each reflection pattern (RP), the current user equipment (UEs) PI, which are widely and easily available in communication networks, are stored. Moreover, for further overhead reduction, and based on the stored PI, we propose a partial PI-CB scheme for PBF of the RIS, where a group of candidate RPs, that are highly probable to serve the UEs, is determined depending on a distance metric. Consequently, the system can select the best RP by training only this group of RPs instead of searching the entire PI-CB. The proposed full and partial PI-CB schemes highly reduce the overhead and complexity, especially in large RIS. Also, they outperform channel estimation and alternating optimization (CE&AO) based and randomly generated CB based schemes in terms of effective achievable rate, particularly in rapidly changing channels. The proposed schemes can obtain about 35% increase in the effective achievable rate compared to CE&AO based scheme in 4 users' scenario with extremely low complexity. In addition, using the partial PI-CB, further reduction in overhead and complexity can be achieved with a slight decrease in performance due to the positioning error.

INDEX TERMS Reconfigurable intelligent surface, passive beamforming, positioning information, codebook.

I. INTRODUCTION

IN THE near future, it is expected that beyond 5G networks will be widely required and desirable to pave the way to a fully connected world through servicing several applications [1] such as mixed reality, holographic communication, automation, massive internet of things, disaster management, etc. Hence, varied requirements should be provided by technologies to enable these networks, e.g., massive data rate up to 1 THz, extremely low latency between 10-100 μs, ultra reliability and mobility, extreme network coverage, and low power consumption. To do so, several investigations are performed on the high frequency bands like millimeter wave (mmWave) [2], terahertz and sub terahertz (sub-THz) [3], [4] spectrums. Furthermore, several technologies have been appeared to assist in construction a robust, usable and stable beyond 5G networks such as multiple input multiple output (MIMO) systems [5], reconfigurable intelligent surface (RIS) [6], stacked intelligent metasurfaces [7], unmanned aerial vehicles (UAVs) [8], and artificial intelligence [9]. The high frequency bands suffer extremely high signal attenuation due to their channel nature [2], [10]. Moreover, due to different obstacle types [11], [12], [13], e.g., static buildings, moving vehicles and humans, the blockage occurrence has a high impact on their received signals.

RIS or intelligent reflecting surface (IRS) is a programable surface, that consists of a high number of elements, usually passive ones to reduce the power consumption of the system. And, by adjusting the amplitudes and the phase shifts of these elements, RIS can reflect the signals incident on it to another direction. The new RIS technology has begun to occupy a crucial role in beyond 5G networks as an aide in mmWave and THz communication networks, because it can overcome the impacts of the attenuation and blockage of these signals, where it provides alternative line of sight (LOS) paths to the transmitter (TX) to connect with the receiver (RX) [7], [14], [15], [16]. Thus, RIS can widen the network coverage, guarantee a higher channel rank and enhance the statistics of the wireless channels. Moreover, RIS may collaborate with UAV in what is called aerial RIS (ARIS) [8] to improve UAV performance in emergency situations and public events' scenarios. Furthermore, modulation schemes, e.g., improved index modulation [17], have been integrated with RIS to enhance the performance of RIS aided wireless communication systems.

To utilize alternative RIS links as helpers for improving the communication systems, a passive beamforming (PBF), is mandatory. In which the RIS elements are configured, i.e., RIS elements' amplitudes and phase shifts values are determined. This PBF process is highly significant because it affects the system complexity and the required overhead, and as a result impacts on the overall performance of the system. Unfortunately, the RIS is usually implemented with passive elements, hence, control signals cannot be exchanged between the communications sides, i.e., TX, RIS and RX, to directly establish the transmission between them as the case between active TXs and RXs. Moreover, the number of RIS elements is high comparable to the antenna elements. Thus, researchers direct their interest to propose new and efficient algorithms to perform the PBF in RIS aided communication systems.

Mainly, the PBF schemes are classified into two categories: firstly, channel estimation (CE) and passive beamforming optimization (CE&O) approaches [18], [19], [20], [21], [22], [23], where pilots' signals are used to estimate the cascaded channels between the communication nodes through RIS, and based on these channels, active and passive beamforming processes are done. However, due to the highly required overhead and complexity for channel estimation and the time necessary to jointly optimize active TX antennas and passive RIS elements, especially with high RIS elements' number, lower complicated and time consumer codebook (CB) based approaches have been suggested. These second category techniques [24], [25], [26], [27], [28], [29], [30], [31] commonly consist of three stages, first, reflection pattern (RP) codebook design phase, then searching through CB codewords stage, and, learning phase, where the system learns the best RP to be used for RIS configuration in transmission period. The CB based solutions can reduce the required overhead and complexity, also they can eliminate the error propagation compared to CE&O schemes, hence achieving a higher performance in terms of the effective rate. Furthermore, these schemes can be easily added to the existing communication architectures. However, to enhance the RIS aided system performance, some issues in CB based schemes, e.g., CB design, searching time, outage, and misalignment problems, should be solved. Consequently, a more efficient codebook design stage is needed, where a CB, that can actually cover the entire area of interest, should be generated. In addition, instead of searching the entire CB, a less complex and lower overhead training algorithm shall be proposed, so that less time will be required for the searching phase.

Fortunately, user equipment context information (CI), and specifically positioning information (PI), has become widely available and accessible in 5G and beyond networks [32]. Because several algorithms can estimate a high accurate UE location within a short time and simple processes depending on the signals broadcasted by the existing technologies. Although these valuable information is susceptible to be attacked by unauthorized parties, recently, many algorithms have been proposed to guarantee the security and the privacy of the PI [32], [33]. Hence, implementing different schemes in 5G and beyond networks using PI to help in relaxing their existing limitations becomes common and more practical [34], [35]. Global positioning service (GPS), Wi-Fi, and visible light communication [36], [37], [38] are examples of the technologies that provide positioning services to the wireless networks in outdoor, urban or indoor environments. Although, the PI comes with an error due to the used service, technique or method [37], [38], searching within a group of RPs can guarantee eliminating this error effect on the performance. In addition, the concept of PI based beamforming (BF) has been previously suggested for active TX antennas beamforming design, and several works proved that PI based BF schemes can obtain good performance with very low complexity and overhead compared to CE based schemes [38], [39], [40].

This work mainly aims to overcome the weaknesses of the existing CB based solutions for PBF depending on the PI, where its novelty is basely depending on first, constructing a new efficient area descriptive and less complicated CB, where the CB design process is performed relying on information generated from the environment of interest. Second, to notably minimize the training complexity, a group of most likely RPs, that can efficiently configure the RIS, is determined depending on the relationship between the CB codewords and the users that will be serviced in the target time frame. Context information, or more specifically PI, can be a promising candidate for constructing such efficient CBs, because it can help in estimating the channels between the BS or the RIS and the coming served UEs. Moreover, based on PI, candidate RPs for searching can be chosen. Specifically, the PBF process is the procedure of configuring the RIS elements in a manner that redirects the incident signal on the RIS into certain locations. Hence, each CB codeword can be linked or associated to specific user equipment (UEs) positions. As a result, designing the CB can be done to include only the scenario's area that UEs are distributed in. Furthermore, the training stage can be enhanced benefiting from the UEs positions stored corresponding to each RP. Relying on the wide accessibility and the already existence of the PI in the wireless networks, the PBF process can be improved aiming to enhance the overall performance of RIS aided communication system by reducing the system required overhead. In addition, CI such as UEs positions, speeds and orientations can be combined to be used as input features to deep learning based PBF schemes, that can efficiently obtain better performance in the RIS aided system, which will be reserved for our future research.

More, specifically, our main contribution in this paper can be summarized in the following points:

- First, we propose a PI based CB for RIS assisted MISO systems considering discrete phase shifts at RIS elements. Specifically, the system designs this CB in the first Q time frames, here, Q represents the CB size and the time frames required for designing the CB. At the beginning of each qth time frame, where $q = 1, \ldots, Q$, a random Q RPs are generated, and the best one of them is selected to serve the UEs in this time frame. Then, the best selected RP and the UEs PI corresponding to this RP are stored in the PI-CB and given an index. After finishing the Q time frames and designing the full PI-CB, the system can directly search this CB to achieve a higher performance with a lower overhead and complexity comparable to the existing channel estimation and alternative optimization (CE&AO) based and random CB based schemes, especially in rapid changing channels and larger RIS. This full PI-CB can efficiently cover the area of interest because it is designed in online phase to describe the environment under consideration.
- In addition, a partial PI-CB scheme is proposed, where the system can further benefit from the stored information and selects a group of candidate RPs, that are highly probable to serve the UEs, and trains only these RPs instead of the entire PI-CB. To do so, the base station (BS) receives the PI of the new UEs, then finds out the RPs, those their corresponding PI highly match with the UEs PI, by calculating and evaluating a distance metric. Then, the system selects the best RP to be used in transmission period using rote learning method. Due to the overhead reduction, this partial PI-CB scheme proves its efficiency in terms of the effective achievable rate, even if a small number of RPs are used for training stage.
- Finally, we prove that the proposed full PI-CB can efficiently work under different environments as the procedure of its design is environment independent. Furthermore, we demonstrate the proposed full and partial PI-CB performance in terms of the effective achievable rate under different dynamically channels' conditions. Also, we discuss the required complexity of the proposed schemes compared to the existing schemes. Moreover, we investigate the effect of using larger RIS in our proposed schemes. Besides, we prove that the positioning error has a slight effect on the proposed partial PI-CB scheme performance. To best of our knowledge, this work is the first study that gives a clear procedure and discussion of using PI in RIS PBF considering both single user and multi-user MIMO scenarios.

The reminder of this paper is organized as follows: In Section II, we review the related works that proposed CE & O based schemes, then we focus on the studies that discussed and proposed CB solutions for PBF. Section III presents the studied multiuser multiple input single output (MU-MISO) system model and the proposed network description. After that, we give a detailed description of the stages required in CB based schemes in Section IV. Meanwhile, Section V illustrates the proposed full and partial PI-CB schemes, where it explains how the PI-CB design stage is performed, then describing the searching stage in the proposed schemes. Section VI presents the simulation parameters, scenarios, and results. Finally, we conclude this paper and suggest possible future directions in Section VII.

Notation: For better convenience, we list the used symbols and notations in this paper in Table 1. Upper-case and lower-case boldface letters $\mathbf{A}$ and $\mathbf{a}$ present a matrix and a vector, respectively, while italic letters refer to scalars. $(\bullet)^H$ represents Hermitian transpose. diag($\mathbf{a}$) is the diagonal matrix where vector $\mathbf{a}$ is on its diagonal. $\mathcal{CN}(\mu,\ \sigma)$ refers to the probability density function of the circularly symmetric complex Gaussian distribution with μ mean and σ^2 variance. For better presentation, we define all used symbols in Table 1.

II. RELATED WORK

To efficiently use RIS as an assistant to communication systems, passive beamforming design is needed. Among many domains studied in the literature, we identified two main directions to perform the PBF process. First, CE and joint beamforming optimization based schemes, and, secondly, codebook based schemes. In the first category, feedback pilots from UE are required as signaling overhead to estimate the direct and reflected channels between TX and RX. Then, based on the estimated channels, the system configures the RIS elements' amplitudes and phase shifts accordingly, after performing joint optimization to determine active and passive beamforming vectors for TX and RIS, respectively.

Many studies have proposed CE and PBF optimization for RIS aided communication systems, e.g., [18], [19], [20], [21], [22]. Authors in [18] proposed three phase pilot based CE scheme aiming to reduce the required system overhead for estimating both the direct RX-TX and reflected RX-RIS-TX channels in uplink multiuser scenario. In [19],

TABLE 1. List of symbols and notations.

Symbol	Description
K / M / N	The number of UEs, BSs antennas, RIS elements.
$\mathbf{G}$ / $\mathbf{h}_{r,k}^H$ / $\mathbf{h}_{d,k}^H$	The BS-RIS channel, the RIS-kth UE, and the BS-kth UE channel.
ϕ_n / $\mathbf{\Theta}$	The phase shift of element n, and the RIS diagonal phase shift matrix,
γ	The reflection coefficient amplitude.
$\mathcal{B}$	The set of discrete phase shifts used at the RIS.
P_{UL} / P_T	The pilot average power and transmit power at the BS.
$\mathbf{z}$ / n_k	The received AWGN at BS / UE k.
${\sigma_z}^2$ / ${\sigma_k}^2$	The noise power at the BS / UE.
$\mathbf{w}_k$ / t_k	The transmit beamforming vector and transmitted information symbol to UE k.
r_k	The downlink received signal at the kth UE.
Q / Q_c	The number of the training slots or the RPs in the CB for the full and partial PI-CB.
$\phi_{n,q}$ / $\mathbf{\Theta}_q$	The phase shift of RIS element n, and the RIS configuration matrix at the qth training period.
$\mathbf{\theta}_q^*$	The selected and stored qth RP in the full PI-CB after the training of the Qth generated RPs CB.
R_q / R_{q_c}	The UEs sum-rate at the qth, and q_cth training period for the full and partial PI-CB.
$\mathbf{P}_q$ / $\mathbf{P}$	The referenced positioning matrix corresponding to the qth RP, and the current UEs positioning matrix.

authors tried to decrease the overhead by exploiting different channel coherence time of TX-RIS and RIS-RX links. A statistical channel state information (CSI) based scheme is proposed in [20] for decreasing the system overhead, at the expense of a lower performance obtained in comparison to instantaneous CSI based methods. Furthermore, any blockage occurrence to the established links using this scheme highly degrades the system performance. In other research, passive beamforming design is also a hot topic; for example, the authors in [21], [22] proposed an iterative algorithm and its modified version to optimize the RIS configuration using estimated channels in RIS aided multiuser MIMO system. Authors in [23] developed an alternative optimization approach to achieve a sub-optimal solution to optimize the active and passive beamforming. Although these modifications in CE and efficient PBF design reduced some of the overhead, the CE and PBF based mechanisms still suffer from high overhead especially in case of large RISs with many elements. Furthermore, active-passive beamforming still requires a long time in online phase, which delays the system.

On the other side, different codebook based schemes have been developed to overcome the existing challenges in CE and PBF optimization based approaches [24], [25], [26], [27], [28], [29], [30], [31]. In CB based schemes, systems need estimating the end-to-end composite channel and designing the TX. Moreover, the best RP in the predefined set, that achieves the best quality of service for UE, shall be selected for configuring RIS. These techniques guarantee low complexity and overhead, achieving also robust and acceptable performance. CB based solutions are performed in three main phases, codebook design, searching stage, and best RP learning stage. Based on a predefined random CB or Euclidean distance maximization CB, authors of [25] proposed a framework to estimate the superposed channel and design the PBF in a less complicated process considering a discrete phase shift practical hardware constrain in RIS aided MIMO system. In [26], the authors developed a channel training based protocol for RIS aided system to estimate the end-to-end channel and configure RIS based on a predefined CB. Authors of [24] discussed the CB based solutions for RIS and focused on its stages. Then, to prove the superiority of CB based schemes, they compared the performance of the conventional random CB based scheme with the optimum CE and PBF optimization based approach. In [27], authors proposed multi-lobe beam training scheme to further reduce CB based approaches overhead, where joint TX and RIS CB are considered. In [28], the authors used predefined hierarchical codebook for beam training in RIS assisted mmWave communication. These works manifest and prove the low complexity and overhead of CB based mechanisms, comparable to CE and PBF optimization based schemes, alongside achieving good performance. However, the designed codebooks are still under question to efficiently serve the UEs in the target area and obtain near optimum performance. Moreover, the required training periods for searching stage, as a result system overhead, are still high due to codebooks' sizes. In addition, [25], [26] still need to estimate the end-to-end channel which is not an easy process. Meanwhile, works in [27], [28] may suffer outage and misalignment due to using the concept of binary and hierarchical search. Moreover, extending these schemes to multi-users scenarios needs the reptation of the searching process for each UE before designing the optimal codeword. In [29], the authors have proposed environment-aware CB that is designed using statistical CSI which is offline calculated based on UE location information. But this scheme still needs high overhead as other CB based solutions. Moreover, the UE location information has not been fully used, as it does not help in constructing a real-time efficient CB or reducing the overhead of the searching stage. Furthermore, some studies as [30] and [31] consider positioning information for proposing codebook based RIS passive beamforming schemes. In spite of the reduction of the required overhead, these proposed schemes need much complexity for CBs design stages. Moreover, the works in [29], [30], [31] only consider the single user scenario and a specific environment, where the CBs are offline generated, hence these CBs cannot be adapted if some changes happened in the environment.

III. SYSTEM MODEL

The network architecture of the RIS aided wireless communications system is presented in Fig. 1. Here, RIS can provide alternative links between BS and UEs for widening the network coverage and eliminating the blockage effect. BS is equipped with a uniform linear array (ULA) antenna, that consist of M elements, aiming to directly establish communication links with K single antenna UEs, or indirectly connect

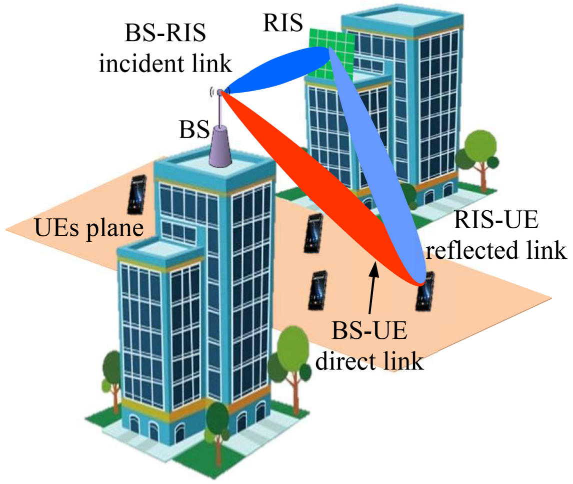


FIGURE 1. The network architecture of RIS aided wireless communications system.

with UEs through the aid of the RIS. The RIS consists of N passive elements, which can be adjusted using a controller connected between the BS and the RIS. The process of determination of RIS elements' amplitudes and phase shifts is the PBF process. Through this study, we consider single user (SU) and multiuser (MU) MISO systems.

Let $\mathbf{h}_{d,k}^H \in \mathbb{C}^{1\times M}$ refer to the direct wireless channel between BS and UE k, $\mathbf{G} \in \mathbb{C}^{N\times M}$ represents the channel between the BS and the RIS, and $\mathbf{h}_{r,k}^H \in \mathbb{C}^{1\times N}$ refers to the channel between the RIS and UE k, where $k = 1, 2, \ldots, K$. Also, $\mathbf{\Theta} = \text{diag}\{\boldsymbol{\theta}\}$ is the RIS diagonal phase shift matrix, where $\boldsymbol{\theta} = [\theta_1, \theta_2, \ldots, \theta_N]^T$ is the RIS reflection pattern (RP), i.e., reflecting beamforming vector at the RIS, and $\theta_n = \gamma e^{j\phi_n}$. We denote by $\phi_n \in [0, 2\pi)$ the phase shift of RIS reflecting element n in continuous case, and $\gamma \in [0, 1]$ is the reflection coefficient amplitude. To follow practical implementation constrains, we consider discrete phase shifts, where ϕ_n can be one of the values in the $B = 2^b$ discrete values set, where b is the number of quantization bits for phase shift values. Moreover, we use uniform quantization to obtain the discrete phase shifts of the RIS elements form the $[0, 2\pi)$ interval, where we assume $b = 4$ to balance between the practical implementation complexity and the obtained system performance [41]. Thus, the set of discrete phase shifts used at the RIS can be presented as:

$$\mathcal{B} = \{0,\ \ \Delta\theta, \ldots, (B-1)\Delta\theta\}, \tag{1}$$

where $\Delta\theta = 2\pi/B$.

For the uplink (UL) phase, which is used for sending feedback from the UEs to the BS in order to estimate channels and determine the best codeword for RIS, BS receives the signal $\mathbf{y} \in \mathbb{C}^{M\times K}$, corresponding to the UL pilots during the UL training. Assuming that the pilot symbol transmitted from UE k to the BS is s_k, where this pilots is a random variable follow standard gaussian distribution, the received signal, $\mathbf{y}$, can be expressed as:

$$\mathbf{y} = \sum_{k=1}^{K}\Big(\mathbf{G}^H\mathbf{\Theta}^H\mathbf{h}_{r,k} + \mathbf{h}_{d,k}\Big)\sqrt{P_{UL}}s_k + \mathbf{z}, \tag{2}$$

where P_{UL} denotes the pilot symbols average power, while $\mathbf{z} \sim \mathcal{CN}(0, {\sigma_z}^2\mathbf{I}_M)$ is the received AWGN at BS, and σ^2 is the noise power.

Regarding downlink (DL) transmission case, BS uses a linear transmit precoding (TPC), hence each UE k will be assigned a separated transmit beamforming (TBF) vector, $\mathbf{w}_k \in \mathbb{C}^{M\times 1}$, so BS transmits a signal, $\sum_{k=1}^{K}\mathbf{w}_k t_k$, to all UEs. Here, t_k is the transmitted information symbol to UE k, and the symbols of UEs are independent random variables with unit normal distribution. Hence, the downlink received signal at the kth UE, r_k, can be expressed as:

$$r_k = \Big(\mathbf{h}_{r,k}^H\mathbf{\Theta}\mathbf{G} + \mathbf{h}_{d,k}^H\Big)\sum_{j=1}^{K}\mathbf{w}_j t_j + n_k, \tag{3}$$

where $n_k \sim \mathcal{CN}(0, \sigma_k^2)$ is the received AWGN at UE k. Hence, the SINR of UE k can be written as:

$$SINR_k = \frac{\left|\Big(\mathbf{h}_{r,k}^H\mathbf{\Theta}\mathbf{G} + \mathbf{h}_{d,k}^H\Big)\mathbf{w}_k\right|^2}{\sum_{j=1,j\neq k}^{K}\left|\Big(\mathbf{h}_{r,k}^H\mathbf{\Theta}\mathbf{G} + \mathbf{h}_{d,k}^H\Big)\mathbf{w}_j\right|^2 + \sigma_k^2}. \tag{4}$$

The active and passive beamforming vectors are designed based on channel estimation or CB training to maximize the target quality of service metric. In this paper, we target maximizing the UEs sum rate by jointly designing the beamforming vectors at the BS and the RIS. Mathematically, this optimization problem (OP) can be formulated as:

$$\begin{aligned}
(O_1)\ \max_{\mathbf{w}\mathbf{\Theta}}\quad & \sum_{k=1}^{K}(1 + SINR_k)\\
\text{s.t.}\quad & \sum_{k=1}^{K}\|p_k\|^2 \leq P_T.\\
& \mathbf{\Theta} = \text{diag}\Big\{\gamma e^{j\phi_1}, \ldots, \gamma e^{j\phi_N}\Big\},\\
& \phi_n \in \mathcal{B}, n = 1, \ldots, N.
\end{aligned} \tag{5}$$

where $\sum_{k=1}^{K}\|p_k\|^2 \leq P_T$ refers to the transmit power constraint at the BS as P_T is the maximum available power. The transmitter beamforming matrix, $\mathbf{W}$, is coupled with the RIS phase shifts matrix, $\mathbf{\Theta}$, in the O_1 objective function (OF), thus making P harder to be solved. On contrast, optimizing $\mathbf{W}$, given the RIS reflection matrix, can follow the same concept of traditional MISO and MIMO systems without RIS existence [42]. Moreover, as the BS and RIS positions are fixed, this $\mathbf{W}$ matrix can be determined using a CE based scheme [43], or any other relevant method that can be found in the literature [37]. Hence, we focus only on determining the $\mathbf{\Theta}$ based on training the full codebook or part of the CB to estimate the end to end composite channel.

IV. CODEBOOK BASED SOLUTIONS

Codebook based schemes consist of three major steps, as follows. At first, designing the RPs codebook step, then, scanning only the CB reflection configurations, where a feedback corresponding to each RP is sent by UE, and, finally, learning stage, which aims to select the best RP to be used for data transmission period. CB based solutions come with many advantages over the existing CE and PBF approaches [24]. It is easier to apply CB based framework to the communication architecture to optimize RIS elements, where the only requirement is to increase the training overhead, but this overhead can be controlled based on the channel's coherence time, hence it must flexibly adapt pilot overhead to any specific scenario. Moreover, codebook based schemes can highly reduce the computational complexity of the system by separating the beamforming of active and passive elements. Also, they can relax error propagation effect as it only occurs at the transmitter side, while designing the beamformer. Furthermore, only $\log_2 Q$ bits control signaling overhead is needed in CB based solutions, hence highly declining the backhaul overhead and delay. Because our PI-CB and proposal mainly depend on the same stages as other CB based schemes, in this section, we will summarize the major points of CB based schemes that serve our idea and motivated us to propose our scheme.

A. CODEBOOK DESIGN STAGE

This stage is crucial to achieve a high system performance with low complexity and overhead. The universal space codebook is the conventional CB that covers the entire searching space with all possible reflection configuration patterns. However, due to its very large size, it is impossible to use this CB. The more intelligent way is to design an acceptable size CB by selecting a subset, containing number of RPs, Q, from the entire universal space. Several CBs designing algorithms have been proposed in previous works such as random CB, Sum Distance Maximization (SDM), and orthogonal CB generation. These CBs try to cover as wider space as possible using low number of codewords, to efficiently serve UEs with their required quality of services.

Random CB generation is the simplest and most straightforward technique, where Q reflection patterns are randomly selected form the universal space without any modifications [25]. In Fig. 2 (a), we give an example of the random CB with $Q = 6$ and $N = 1$. Unfortunately, this CB has many limitations as it cannot efficiently cover the searching space of interest, its achieved performance is not stable due to the randomness of the chosen RPs at each time instance. Furthermore, due to its size, it is still inconvenient to use it within the limited time allocated for the training process. Sum distance maximization CB seems to be promising as it can achieve a moderate gain using a low number of codewords [26], as it is shown in Fig. 2 (b) for the case $Q = 6$ and $N = 1$. However, this heuristic technique cannot guarantee covering the area of interest and reaching the convergence point quickly, especially with a high number of RIS elements and higher number of discrete values, e.g., 16 value. Furthermore, the size of this CB is still large, similar to random CB size. Orthogonal CBs are another method to provide more accurate channel estimation, e.g., DFT based beam steering that has been proposed in [17]. However, these CBs still suffer the same issues regarding the system overhead and complexity as the previous two CBs. An example of orthogonal CB with $Q = 2$ and $N = 2$ is presented in Fig. 2 (c). In addition to the previous issues, the existing codebooks are designed in offline phase without any knowledge about the environment. Furthermore, generating these CBs, in online phase, every time frame by selecting different set of RPs to better present the entire space cannot guarantee better performance. Moreover, this CB regeneration phase will increase system delays, especially in the case of SDM CB which needs time to achieve convergence.

B. SEARCHING STAGE

In this step, the system examines all the existing codewords in the predefined CB. First, the transmitter sends the identification (ID) of each RP to RIS to configure its elements according to it, i.e., adjusting RIS elements' amplitudes and phase shifts. Then, it receives a feedback signal from the receiver containing some information, usually regarding the received power at the RX corresponding to each codeword. The total searching overhead of CB based schemes is $O(Q)$, where Q is the CB size, while their computational complexity is $O(QMK^3)$. Thus, there is a tradeoff between the obtained system performance and overhead. Moreover, a vital question appears, why searching the entire CB, if the system can decrease searching overhead by only examining a group of candidate RPs, that are highly probable to serve RX.

C. LEARNING STAGE

Based on the feedback from the Q observation, the transmitter can determine the best RP for downlink transmission period. Learning optimum RP aims to select the codeword that achieves maximum objective function. This OF varies depending on the final system goal, e.g., obtaining maximum achievable rate, minimum delay, etc. Different learning methods can be used for this purpose, e.g., rote learning, fusion learning, and machine learning, but all of them depend on RPs observations. Rote learning stores all observations and simply selects the one that maximizes the OF. On contrast, fusion learning weights multiple RPs observations, then combines them to define the best RIS codeword. Although this mechanism outperforms rote learning in case of convex optimization problems, it will increase the RIS control signaling overhead to Q bits. Moreover, it highly relies and designed based on the target OF. Meanwhile, machine learning approaches, whether they are supervised, unsupervised, or reinforcement learning, can also be utilized to determine the suitable RP using the pre-trained or online training neural network. Generally, the learning stage is still a big open direction for further investigation, but it is out of

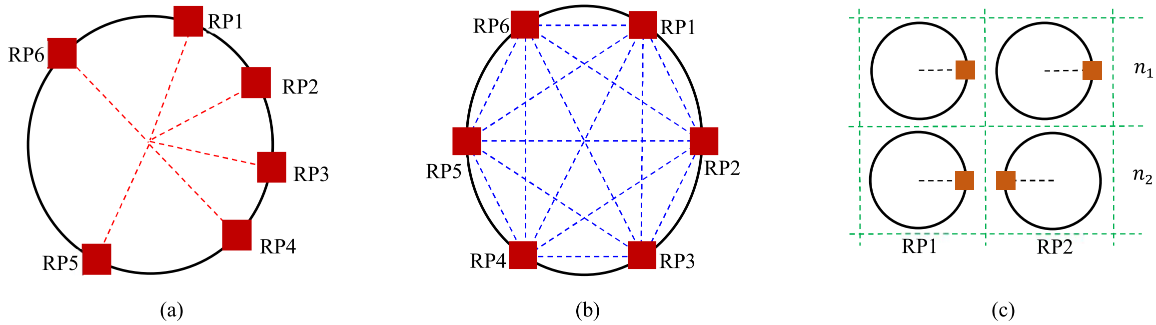


FIGURE 2. Example of (a) random CB (Q= 6 and N= 1), (b) SDM-CB (Q= 6 and N= 1), and (c) Orthogonal CB (Q= 2 and N= 2) generation in CB-PBF schemes.

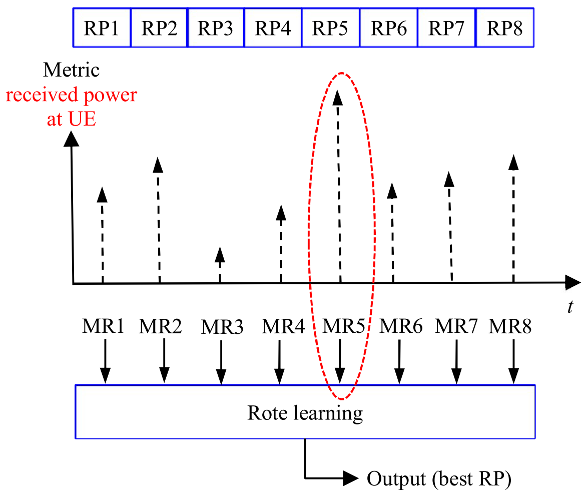


FIGURE 3. Rote learning in CB-PBF schemes.

scope of our present work, therefore we adopt the simplest rote learning approach to select the best RIS codeword. Fig. 3 presents an example of rote learning mechanism with $Q = 8$; more details about other methods can be found in [24]. The challenges in CB design and searching stages motivate us to the idea of designing environment related CB, then restrain the search only through a group of this CB codewords, which can be chosen depending on RX context information, e.g., positioning information, hence reducing system overhead as we will describe in the following section.

V. PROPOSED PI BASED CODEBOOK SCHEMES

In this section, we discuss the proposed positioning information based codebook scheme for RIS PBF. First, we present the procedure used to design the full PI-CB, then explaining how this CB can be used for training and best RP learning stages. Meanwhile, in the second subsection, we illustrate the proposed framework for the partial PI-CB scheme. Our schemes contribute to the first and second stages of the existing CB based schemes. First, the full PI-CB proposal aims to design a positioning related CB in an online process which is only performed at the first Q time frames of the system. Hence, the system can construct a descriptive and an environmental-aware codebook that can efficiently cover the area of interest. This CB is an environmental centric one, hence it can be adapted to different applications and scenarios such as scalable wide band scenarios [44]. Furthermore, relaying on the stored referenced PI in the full PI-CB, the searching stage is further improved by performing training through only a group of Q_c candidate codewords instead of examining the entire CB, as in the case of using the conventional CB based schemes. Consequently, a novel partial PI-CB scheme is proposed. The proposed full and partial PI-CB schemes can enhance the long term performance of the system and highly reduce the required overhead.

A. PROPOSED FULL PI-CB DESIGN AND LINK ESTABLISHMENT

When a new UE requests to connect to the network and the BS has a free resources to provide the UE with, it sends an acceptance to indicate to the UE to send its current position. This PI can be easily available using GPS or Wi-Fi services depending on the network environment. Also, this information is transferred using the control plane which can be any wireless band, e.g., Wi-Fi. Hence, this process happens without additional overhead to the used 5G and beyond communication band. Simultaneously, the system generates Q random configurations for RIS elements phase shifts from the universal space set which can be written as:

$$\phi_{n,q} \sim \mathcal{U}(\mathcal{B}), \ \ q = 1, \dots, Q, \ \ n = 1, \dots, N. \tag{6}$$

During the qth training period, the system uses the RIS controller to adjust the RIS elements using the configuration of the qth RP. The BS sends the transmitted signal and waits for feedback from the UEs containing information regarding their received signals. Following the same channel training based protocol that have been proposed in [26], and assuming $\mathbf{\Theta}_q$ as the RIS configuration matrix at the qth training period, the received signal of the lth time slot of the qth training period can be expressed as:

$$\begin{aligned} y_{q,l} &= \sum_{k=1}^{K}\left(\mathbf{G}^H {\mathbf{\Theta}_q}^H \mathbf{h}_{r,k} + \mathbf{h}_{d,k}\right)\sqrt{P_{UL}}s_{k,l} + \mathbf{z}_{q,l} \\ &= \sum_{k=1}^{K} \mathbf{h}_{q,k}\sqrt{P_{UL}}s_{k,l} + n_{q,l} = \sqrt{P_{UL}}\mathbf{H}_q\mathbf{s}_l + \mathbf{z}_{q,l}, \end{aligned} \tag{7}$$

where $\mathbf{h}_{q,k} = \mathbf{G}^H {\boldsymbol{\Theta}_q}^H \mathbf{h}_{r,k} + \mathbf{h}_{d,k}$ refers to the superimposed direct and cascaded links between the UE and the BS at qth training period. $S_{k,l}$ is the transmitted pilot symbol from UE k at lth time slot. Meanwhile, $\mathbf{H}_q = [\mathbf{h}_{q,1}, \mathbf{h}_{q,2}, \ldots, \mathbf{h}_{q,K}]$ is the superimposed UEs-RIS-BS channel. Hence, after collecting the signals of L time slots, the received signal at the BS in the qth period can be written as:

$$\mathbf{Y}_q = [\mathbf{y}_{q,1}, \mathbf{y}_{q,2}, \ldots, \mathbf{y}_{q,L}] = \sqrt{P_{UL}} \mathbf{H}_q \mathbf{S} + \mathbf{Z}_q, \tag{8}$$

where $\mathbf{S} = [\mathbf{s}_1, \mathbf{s}_2, \ldots, \mathbf{s}_L]$ refers to the pilot matrix from the K UEs to the BS, and $\mathbf{Z}_q = [\mathbf{z}_{q,1}, \mathbf{z}_{q,2}, \ldots, \mathbf{z}_{q,L}]$ is the noise matrix at the BS during the qth period. The channel estimation in the qth period can be done using LS following [26] as:

$$\hat{\mathbf{H}}_{q,LS} = \frac{1}{K\sqrt{P_{UL}}} \mathbf{Y}_q \mathbf{S}^H. \tag{9}$$

Hence, $\hat{\mathbf{h}}_{q,k}$ can be defined, and as a result, UEs sum-rate at the qth time period, R_q, can be expressed as:

$$R_q = \sum_{k=1}^{K} p_k \log_2 \left(1 + \frac{\left| \hat{\mathbf{h}}_{q,k}^H \mathbf{w}_{q,k} \right|^2}{\sum_{j=1, j \neq k}^{K} \left| \hat{\mathbf{h}}_{q,k}^H \mathbf{w}_{q,j} \right|^2 + \sigma_n^2} \right). \tag{10}$$

The system examines all Q RP and memorizes the UEs sum-rate corresponding to each RP. After that, it performs the learning stage, i.e., selects the best RP that can maximize the learning metric, which is the sum rate of UEs, that expressed in (5). This learning phase is similar to the one explained in Fig. 3 except that it uses different metric and CB size.

Next, the best selected RP and UEs positioning information corresponding to this RP will be stored in the PI-CB, $\mathbf{C}$, as reference for further usage, and will be given an index q, where $q = 1, \ldots, Q$, where Q is the size of our proposed designed CB. The codebook size Q is a design parameter that effects on the system final performance, thus choosing another value should be done carefully to maintain balance between system performance and complexity as we will further discuss. In the PI-CB, $\boldsymbol{\theta}_q^*$ presents the selected qth RP, while $\mathbf{P_q} \in \mathbb{C}^{K \times 3}$ is the referenced positioning matrix corresponding to the qth RP, which contains UEs PI. In single user case, the $\mathbf{P_q}$ will be a row matrix contains the coordinates of one UE position, i.e., $\mathbf{p}_q = left[x_q, y_q, z_q]$, meanwhile in multiuser case, $\mathbf{P}_q$, will include all referenced UEs PI, and can be expressed as:

$$\mathbf{P}_q = \begin{bmatrix} x_{q,1} & y_{q,1} & z_{q,1} \\ x_{q,2} & y_{q,2} & z_{q,2} \\ \vdots & \vdots & \vdots \\ x_{q,K} & y_{q,K} & z_{q,K} \end{bmatrix} = \begin{bmatrix} \mathbf{p}_{q1} \\ \mathbf{p}_{q2} \\ \vdots \\ \mathbf{p}_{qK} \end{bmatrix}, \tag{11}$$

where $\mathbf{p}_{q_k} = [x_{q,k} \; y_{q,k} \; z_{q,k}]$ is a row vector which refers to the coordinates of the kth UE position corresponding to qth RP. For simplicity, we assume that UEs plane is constant at 1m height. The proposed full PI-CB can be presented as in Table 2. This CB is flexible and adaptable; hence it can efficiently and easily be constructed in any environment.

TABLE 2. Proposed designed full PI based codebook.

Index	1	2	q	...	$Q-1$	Q
Positioning matrix	$\mathbf{P}_1$	$\mathbf{P}_2$	$\mathbf{P}_q$	...	$\mathbf{P}_{Q-1}$	$\mathbf{P}_Q$
PBF vector	$\boldsymbol{\theta}_1^*$	$\boldsymbol{\theta}_2^*$	$\boldsymbol{\theta}_q^*$	...	$\boldsymbol{\theta}_{Q-1}^*$	$\boldsymbol{\theta}_Q^*$

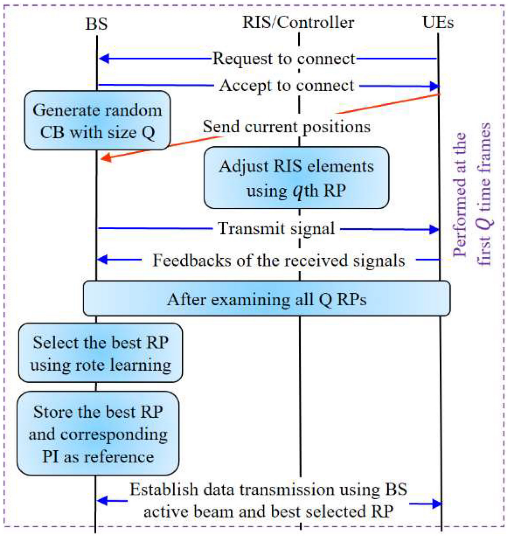


FIGURE 4. The procedure of the proposed full PI-CB scheme.

In the performance evaluation section, we will give two scenarios as examples. The proposed full PI-CB scheme is presented in Fig. 4. It is worth to mention that in the first Q time frames, this phase presents both CB design and BS-RIS-UEs link establishment protocol. Hence, on it, the performance, computational complexity and overhead of the system equalize those of the random CB based scheme. In other words, the total training overhead of the full PI-CB scheme is $O(QK)$, while their computational complexity is $O(QMK^3)$.

B. PROPOSED PARTIAL PI-CB SCHEME

In the partial PI-CB scheme. Firstly, UEs positioning information is obtained by one of the several available service in the network. Then, it is transferred to the BS and stored in current positioning matrix, $\mathbf{P} \in \mathbb{C}^{K \times 3}$, which can be expressed as:

$$\mathbf{P} = \begin{bmatrix} x_1 & y_1 & z_1 \\ x_2 & y_2 & z_2 \\ \vdots & \vdots & \vdots \\ x_K & y_K & z_K \end{bmatrix} = \begin{bmatrix} \mathbf{p}_1 \\ \mathbf{p}_2 \\ \vdots \\ \mathbf{p}_K \end{bmatrix}, \tag{12}$$

where $\mathbf{p}_k = [x_k \; y_k \; z_k]$ is a row vector which represents the coordinates of the kth UE position. This matrix becomes $\mathbf{p} = [x_u, y_u, z_u]$ in single user case. The difference between the positioning services is that each one provides UE location with different standard deviation error. However, the PI-CB is constructed online with the same type of errors, i.e., same conditions effect on referenced positioning matrix, $\mathbf{P}_q$. Hence, these errors are involved in it, so they do not highly impact on the final performance as we will describe in the results section.

If the BS adapts SU MISO system, it calculates the Euclidean distances, as metrics, between UE current PI matrix, $\mathbf{p}$, and the $\mathbf{p}_q$ of all Q RPs as:

$$\mathbf{d}_q^s = \|\mathbf{p} - \mathbf{p_q}\| = \sqrt{(x_u - \mathbf{x}_q)^2 + (y_u - \mathbf{y}_q)^2 + (z_u - \mathbf{z}_q)^2}. \tag{13}$$

On the other hand, if the multiuser scenario is adapted, this distance metric cannot directly be used, e.g., using the norm between the two matrices, $\|\mathbf{P} - \mathbf{P}_q\|$, to calculate the distance or the similarity between the matrices. Because rows in $\mathbf{P}$ or $\mathbf{P}_q$ matrices maybe switched from one RP to another, i.e., similar UEs positions are located in different rows' indices. Hence, it is more suitable to consider all possible matrices' arrangements. Consequently, the proposed metric is to find the summation of all distances between all possible rows' patterns for each qth RP. This metric, $\mathbf{d}_q^m$, can be represented as:

$$d_q^m = \sum_{k=1}^{K} \sum_{j=1}^{K} \|p_k - p_{q_j}\|. \tag{14}$$

In case of choosing one RP as a candidate RP for configuring RIS, the RP that achieves the minimum distance, $\min d_q^s$, or minimum distances summation, $\min d_q^m$, will be selected as the best RP in single user or multiuser scenario, respectively. However, due to the localization error, selecting one RP will degrade the final performance. Hence, we consider constructing a group of candidate codewords, which their P_q have the nearest coordinates to the current positioning matrix, i.e., their d_q^s or d_q^m are the lowest, and as a result these RPs are highly probable to be used for RIS configuration in data transmission period.

Subsequent, our metrics are sorted, and the first Q_c RPs are chosen as a group of candidate RPs. Hence, the system just needs to train these candidate Q_c RPs to find the best one, so it sends the RP index to the RIS to adjust its elements using this RP. Then, the BS transmits a signal and waits for the UEs feedback. Thereafter, UEs sum-rate at the q_cth time period, R_{q_c}, is calculated using the same steps as described in previous sub section for R_q. After examining all Q_c RP, the system can select the best RP, which will maximize the UEs sum rate, for data transmission period using rote learning method. Here, Q_c is a design parameter that should be efficiently chosen to balance between the performance and system complexity.

To determine a Q_c candidate RPs, the required system complexity will be $\mathcal{O}(Q(K^2(n^2+1)-1)+Q\log Q)$, where $\mathcal{O}(K^2(n^2+1)-1)$ represents the complexity order to calculate the distance matrices for each qth RP, and $Q \log Q$ is the complexity for sorting them. After performing rote learning method, the data transmission period will be established using the best active BS beam and the best selected RP

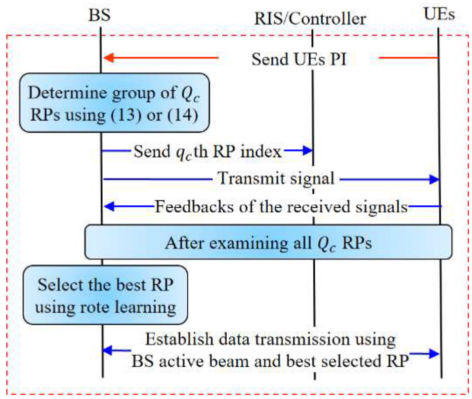


FIGURE 5. The proposed partial PI-CB scheme.

using our algorithm. Fig. 5 summarizes the sequence of the framework of the proposed partial PI-CB scheme. This scheme reduces the overhead to $\mathcal{O}(Q_c K)$ and the overall computational complexity to $\mathcal{O}(Q(K^2(3^2+1)-1)+Q\log Q+Q_c MK^3)$. It is worth mentioning that the frame structure of the proposed protocol is similar to that of CB based schemes, except that the number of training symbols will be lower in our protocol due to using a group of candidate RPs. Selecting the optimal number of candidate RPs is crucial for the partial PI-CB scheme, because Q_c has a high effect on the system computational complexity and training overhead, and as a result on the overall system performance. Hence, we will study Q_c parameter versus the possible obtained system performance in the next section. Fortunately, due to the environment-aware nature of the proposed partial PI-CB scheme, it can be easily adapted and integrated in mobility scenarios to serve moving UEs. For example, in case of UEs movement, the new UEs PI, and maybe other CI such as UEs speed and orientation, can be fed again to the partial PI-CB scheme, thus, a new group of candidate RPs can be chosen for the training stage. Moreover, deep learning algorithms can be helpful in such cases, however, it is out of our work scope, hence we will leave these extensions to our future work.

VI. SIMULATION RESULTS

This section illustrates the outperformance of the proposed positioning information based codebook and its searching protocol comparable to the two benchmarks schemes, the CE and PBF optimization scheme, and the random CB based scheme. For PBF optimization, we consider alternating optimization proposed in [21]. The results show the high performance of our proposal in terms of effective achievable rate and system overhead. Also, we prove the superiority of the proposed CB even if the number of RIS elements are increased or in case of rapidly changing channels. Furthermore, we discuss the performance of the proposed PI-CB framework for PBF, where we present mainly the achievable rate of the system versus using different number of candidate codewords. Moreover, we study the impact of

TABLE 3. Simulation parameters.

Parameter	Value
BS signal power	0.001 Watt
BS / RIS / UEs heights	50m / 30m / 1m
Path-loss exponents for BS-UEs, BS-RIS and RIS-UEs channels	3.5, 2.2, 2.7
Rician factors for BS-UEs, BS-RIS and RIS-UEs channels	0 dB, 10 dB, 3 dB
Number of TX antennas	16
Channel coherence time	500
Noise power spectrum density	-160 dBm/Hz
System bandwidth	10 MHz

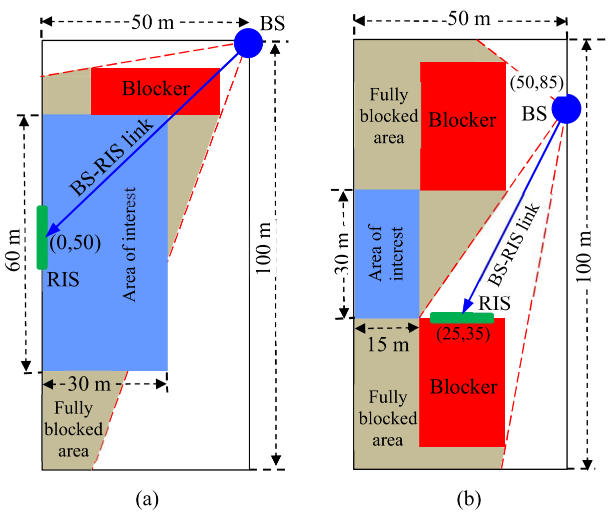


FIGURE 6. The description of the studied (a) first scenario and (b) second scenario.

channel coherence time on our searching protocol. Hence, we can argue about the suitable number of used RPs in searching stage to balance between system overhead, complexity and performance. In addition, as our CB is constructed based on positioning information, which is generally obtained with error, we evaluate the robustness of the proposed scheme oppose to different localization accuracy.

A. SCENARIOS AND SIMULATION PARAMETERS

In this section, we consider both RIS assisted SU and MU MISO systems. The simulation parameters are summarized in Table 3. Meanwhile, Figs. 6 (a) and (b) show the area of interest and the detailed description of the two studied scenarios. Here, we studied two different area of interest, in the first scenario (S1), the area of interest is wider, while the BS-RIS and RIS-UEs links are shorter in the second scenario (S2) than the first one. These changes will impact on the system performance, especially in multiuser cases. However, the proposed scheme still maintains a promising performance even with these environment changes, hence we can note that the proposed scheme can efficiently work in different cases, i.e., it is environment independent, as we will further illustrate in the results. In both scenario, UEs are uniformly distributed in the area of interest. 50,000 Monte-Carlo trials and 100 realization is performed to eliminate the randomness effect of channels, localization accuracy, and UEs positions.

B. RESULTS

Figs. 7 (a), (b), and (c) show the performance of the proposed PI based CB scheme comparable to the benchmarks, CE&AO based, and random CB based approaches. Here, we consider the two previously described scenarios with adapting single user, 2 UEs and 4 UEs MISO use cases. Also, we assume RIS has 80 passive elements. In general, the proposed PI-CB scheme outperforms the random CB based solution performance in all UEs cases in the two scenarios though the same searching complexity is required. Because PI-CB mainly benefits from environmental circumstances, i.e., UEs context information, to construct a more real and descriptive CB and as a result it can efficiently depict the area of interest and cover it. For sure, increasing the codebook size will enhance the achievable rate at the expense of the system overhead, hence a balance between CB size and required performance is needed.

The proposed approach obtains a near optimal performance, which is achieved using optimization method, with acceptable complexity. In addition, its performance nearly saturates, clearer in MU-MISO cases, after a certain number of CB reflection patterns, which is slightly related to the environment under study. For example, it is around 75 RPs and 65 RPs in the first and second scenarios, respectively. That means a wider environment needs a larger CB size to efficiently cover it. However, with a wide 900 m2 area in the first scenario, the CB size is still highly acceptable especially in multiuser scenario which is more complicated. Although the CE&AO scheme achieves higher rates in all cases, this is not true, because the channel is considered a time-invariant which is an impractical assumption. Hence, we will study the effect of the dynamic channel later.

In Fig. 7 (a), because the channel conditions of S2 is better than that of the first scenario, i.e., stronger received power due to shorter BS-RIS and RIS-UE links, all schemes can obtain a higher achievable rate. But the main trends of the schemes are still the same. The achieved rates, using an 80 RP in the proposed PI-CB scheme, are larger than those achieved by random CB based scheme with 0.45 and 0.53 bps/Hz when considering first and second scenarios, respectively. At the same time, the obtained 6.91 and 7.38 bps/Hz rates using the PI-CB approach, with size 80 RPs, present 92.5% and 93.8% of the achievable rates those can be obtained using the complicated alternative optimization method.

In Figs. 7 (b) and (c), it is clearer that the shorter links in the second scenario badly affect the system performance of the two benchmarks and the proposed one due to the interference effect, especially in the 4 UEs case. But the proposed scheme could adapt with the narrow area and maintain performance over the random CB approach and near optimal one. For instance, using 75 RPs CB, the PI-CB approach achieves 10.56 and 10.11 bps/Hz achievable rates

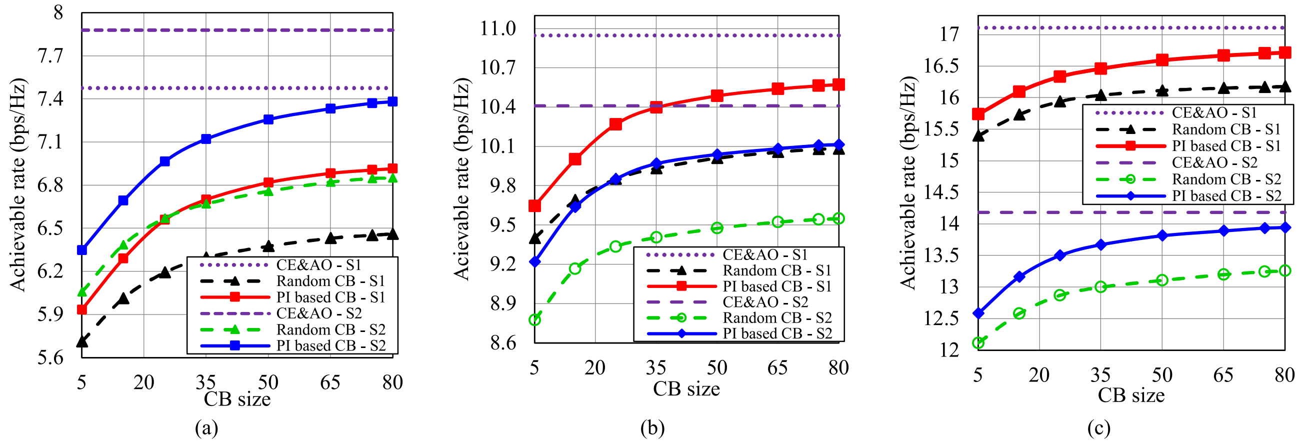


FIGURE 7. The performance of the proposed PI-CB scheme in comparison to CE&AO and randomly generated CB based schemes, in the first scenario (S1) and second scenario (S2) in case of (a) single user, (b) 2 UEs, and (c) 4 UEs.

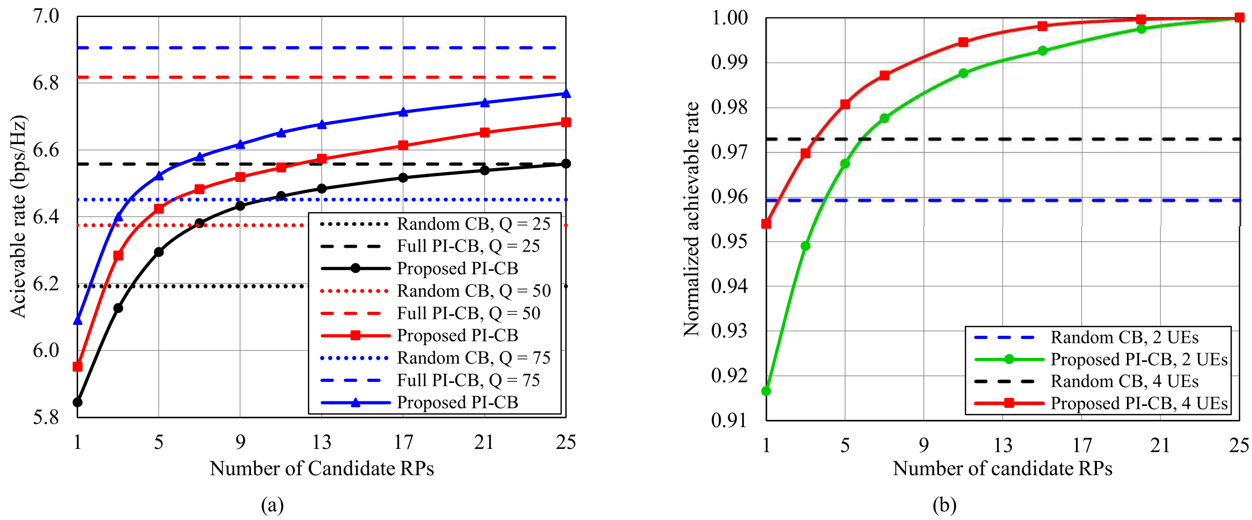
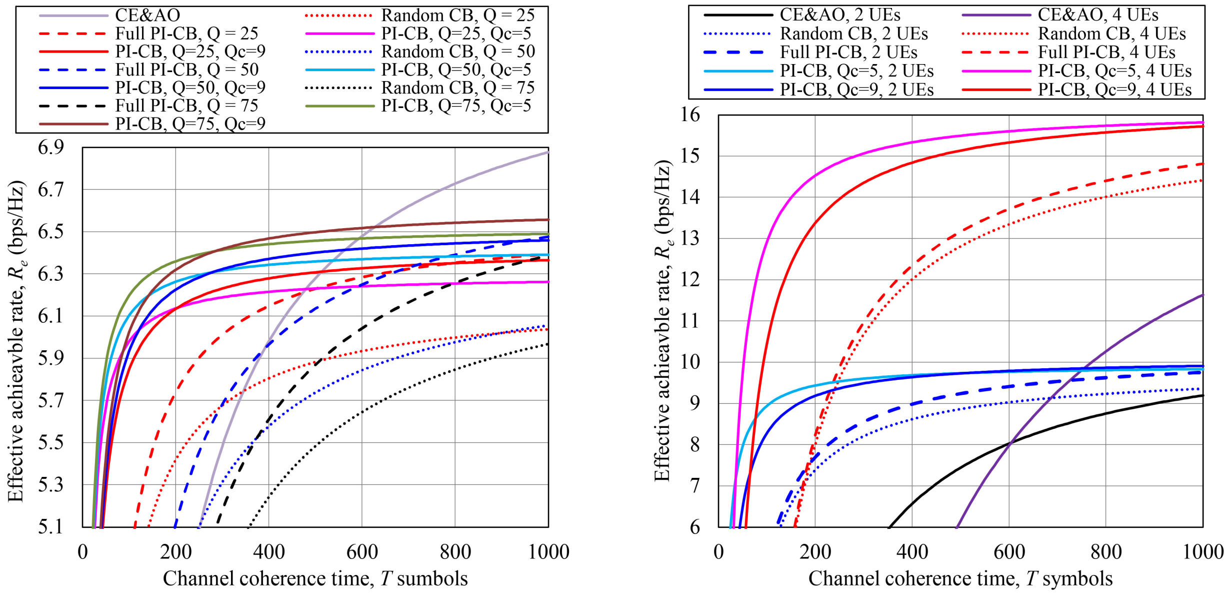


FIGURE 8. (a) the achievable rate of the proposed PI-CB scheme in SU use case assuming different CB sizes, (b) the normalized achievable rate of the proposed PI-CB scheme in MU use case with Q= 25, versus different number of candidate RP.

in 2 UEs case, which are nearly 96.5% and 97.1% of the rates that can be obtained if the optimization method is adapted, in first and second scenarios, respectively. Meanwhile, in the 4 UEs use case, the proposed scheme obtains 16.7 and 13.93 bps/Hz rates using 75 codewords in first and second scenario, respectively, which are about 97.6% and 98.2% of the achievable rates those can be obtained by CE&AO scheme.

Fig. 8 (a) presents the achievable rate of the proposed PI-CB scheme when using different number of candidate reflection pattern, Q_c, instead of training the entire PI-CB in SU use case assuming different CB sizes. This study proves that further reduction can be done to system overhead while maintaining a good performance. First, increasing the number of candidate RPs, with fixing CB size, guarantees a higher achievable rate. Moreover, selecting 5 candidate RPs or more from PI-CB can obtain a higher rate comparable to searching along the entire random CB. For instance, using 1/5 searching complexity, i.e., $Q = 25$ and $Q_c = 5$, the proposed scheme obtains 6.29 bps/Hz achievable rate while random CB based scheme achieves only 6.19 bps/Hz. In addition, constructing a larger CB achieves better performance with a slight increase in overhead and complexity to build it. For example, if CB size of 50 is used instead of 25, a same 5 candidate RPs PI-CB can increase the achievable rate with 0.13 and 0.23 bps/Hz comparable to $Q = 25$ PI-CB and random CB, respectively. Moreover, with a lower number of candidate RPs using larger CB, the system can achieve better performance. For instance, with $Q = 75$ and $Q_c = 7$, the proposed scheme can nearly achieve the same rate, 6.58 bps/Hz, as full $Q = 25$ PI-CB.

Fig. 8 (b) presents the normalized achievable rate in the MU use cases, where we divide the rate obtained using certain number of candidate RPs, or full random CB, over the achievable rate obtained using training the full PI-CB, fixing Q at 25. Again, the same characteristics and notes can be



(a) (b)

FIGURE 9. **The effective achievable rate of the proposed PI-CB schemes using full CB or partial PI-CB compared to CE&AO and random CB cased schemes, when Q_c equals 5 and 9, (a) in SU scenario assuming different CB sizes, (b) in MU scenario assuming Q = 25.**

written for MU cases. For example, if $Q_c = 5$, the proposed scheme guarantees 9.93 and 16.14 bps/Hz achievable rates for 2 UEs and 4 UEs cases, respectively, which are 96.75% and 98.05% of the rates, that can be obtained by searching the entire PI-CB, that are 10.26 and 16.46 for 2 UEs and 4 UEs cases, respectively.

In Fig. 9 (a) and (b), we discuss the effective achievable rate of the system when adapting different PBF schemes, i.e., full and partial PI-CB, CE&AO based, and random CB based schemes, for SU and MU scenarios, respectively. For the partial PI-CB scheme, we consider using 5 and 9 RPs as candidate codewords for training. This study aims to clarify the effect of the reduction of the system overhead using the proposed schemes comparable to the existing schemes in literature. Moreover, it explains how different PBF schemes work against dynamically changing channels. Specifically, the previous superiority of the CE&AO approach assumes invariant-time channel, where system has unlimited slots for estimating full channel and perform optimization for PBF, which is not true in the real world. Consequently, we take into consideration the required system overhead to establish the communication link between BS and UEs through the RIS when evaluating the performance of the PBF schemes.

In single user scenario, Fig. 9 (a), the proposed full and partial P-CB schemes outperform the CE&AO approach in rapidly changing channels, i.e., when $T < 500$, because they cause lower overhead. Moreover, they achieve a higher effective rate than randomly generated CB scheme in general. For example, when $T = 400$, the proposed full PI-CB provides 6.14 bps/Hz using 25 codewords, while only 5.96 bps/Hz can be provided using the CE&AO scheme with extremely higher complexity. Furthermore, using the proposed partial PI-CB scheme under the same conditions, and $Q_c = 9$, the effective rate can be enhanced to be 6.28 bps/Hz. In addition, when adapting larger CB with the same number of candidate RPs, the system achieves a higher effective rate, because larger PI-CBs assure better description for the area of interest. For instance, with $Q = 75$ and $Q_c = 9$, the system obtains 6.47 bps/Hz effective rate.

Although increasing the number of UEs impacts on the performance of all algorithms, Fig. 9 (b), the CB based approaches withstand better, because they still use lower number of slots in searching stage. In contrast, the CE&AO method performs worse even with high channel coherence time cases, because estimating full channel needs a higher number of time slots. For instance, even if $T = 400$, the proposed PI-CB can provide a higher effective rate than CE&AO and random CB schemes, where it provides 9.75 and 14.7 bps/Hz rates using 25 RPs in 2 UEs and 4 UEs scenarios, respectively, meanwhile, CE&AO method provides only 9.43 and 11.6 bps/Hz at the same cases, respectively. Moreover, further reduction of the overhead based on the proposed partial PI-CB can obtain higher effective rate, especially in 4 UEs scenario, because the overhead in the proposed partial PI-CB scheme is $\mathcal{O}(Q_cK)$, while the full CB required overhead equals to $\mathcal{O}$(QK). For example, when $K = 4$, $Q_c = 9$ and $T = 1000$, the proposed partial PI-CB obtains 15.72 bps/Hz which is higher than 14.79 bps/Hz, 14.14 bps/Hz and 11.57 bps/Hz rates those can be achieved using full PI-CB, random CB and CE&AO approaches, respectively. Another interesting point is that increasing the number of candidate RPs obtains a lower effective rate in almost all channel cases, which is different than the case with single UE, because higher overhead will be needed in MU scenarios.

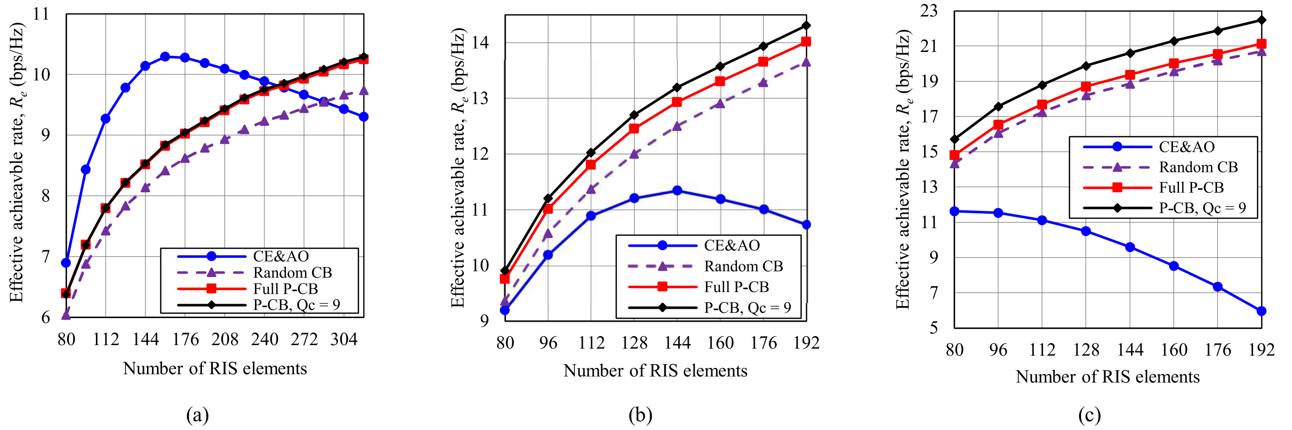


FIGURE 10. **The effective achievable rate of the proposed PI-CB comparable to CE&AO and random CB versus number of RIS elements, consider CB size of 25 RPs: (a) single user, (a) 2 UEs, and (c) 4 UEs MISO systems.**

Depending on Fig. 8 and Fig. 9 results, at least 5 candidate RPs from the PI-CB, considering the CB size equals to or larger than 25, should be selected to obtain a better performance than the one obtained using random CB scheme or CE&AO schemes. Moreover, increasing the number of candidate RPs to 9 can guarantee a better and more stable effective achievable rate in medium and slow changing channels, especially for single user case as shown in Fig. 9 (a). Furthermore, when using a larger initial CB, there is a tradeoff between the obtained performance and the required computational complexity to determine the group of the candidates RPs. This complexity, $\mathcal{O}(Q(K^2(n^2+1)-1)+Q\log Q)$, linearly increases with larger CBs, hence it is preferable to use suitable CB size not larger than 75 RPs, because the enhancement in achievable rate is low and does not worth complicate the system. Moreover, it is worth mentioning that using smaller groups of candidate RPs in the partial PI-CB scheme will achieve higher effective achievable rates in rapidly changing channels and multiuser scenarios.

In Figs. 10 (a), (b), and (c), we evaluate the performance of the proposed full and partial PI-CB comparable to the CE&AO scheme and randomly generated CB scheme in terms of the effective achievable rate, R_e, versus different number of RIS elements. Here, we assume the channel coherence time is 1000 and the CB size for random and PI based codebooks is 25 RPs. Also, we are considering selecting 9 candidate RPs for the partial PI-CB. It is notable that the CB based protocols have an incremental performance with increasing the number of RIS elements, though they don't estimate the full channel or perform PBF optimization. Because the overhead of CB based protocols, $\mathcal{O}$(QK), do not relay on N, in contrast, increasing the number of RIS elements highly effects on the overhead for CE based method and as a result on its performance. Also, with the increase of RIS elements number, particularly in multiuser case, the difference between the effective rates of the proposed schemes and the CE&AO scheme increases, e.g., with N equals 144 and 96 in 2 UEs and 4 UEs cases, respectively. Because the high required overhead wastes the achieved enhancement of the achievable rate using the CE based schemes.

For single user scenario, in Fig. 10 (a), the coherence time can be considered large comparable to the required overhead of the CE&AO scheme, it outperforms CB based protocols. However, with RIS elements larger than 160, its performance begins to decrease until the point, $N = 256$, where it will obtain lower effective achievable rate than the two proposed CB protocol. Because the overhead becomes large comparable to the achievable rate and channel coherence time, in which $R_e = (1-256/1000)*13.14 = 9.778$ bps/Hz. Also, if the channel rapidly changes, $T < 400$, the CE&AO will poorly behave due to full CE even with low N, as we discussed.

In multiusers scenarios, Fig. 10 (b), it is clear how CB based scheme outperforms the CE&AO scheme, especially our proposed full and partial PI-CB, this is a result of the high required overhead for CE. Moreover, it is notable that using 9 candidate RPs further enhances the performance comparable to searching the entire PI-CB or random CB, because the partial PI-CB proposal guarantees lower required overhead. For example, in 2 UEs scenario, with N equals 144 and 192, the proposed partial PI-CB has 13.19 and 14.31 bps/Hz effective achievable rate, which are 1.85 and 3.58 bps/Hz over those can be obtained using the CE&AO method, respectively. In addition, in 4 UEs scenario with $N = 80$, the proposed full and partial PI-CB can obtain 3.18 and 4.1 bps/Hz higher effective achievable rate than the CE&AO scheme, respectively, and this difference further rises when RIS has more elements.

Unfortunately, not only, the required overhead causes the system delay and complexity, but also the optimization method itself requires high computational complexity to determine configuration pattern for RIS with massive elements. AO method is applied with a complexity, $\mathcal{O}(N_i N^{4.5})$, here N_i refers to the number of iteration in AO method [23].

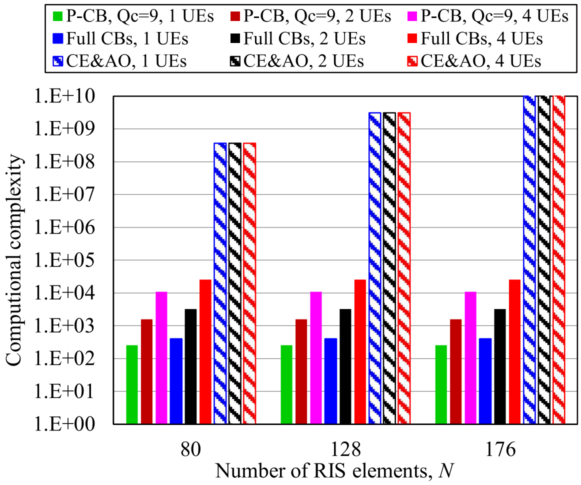


FIGURE 11. The complexity order of RP determination using the proposed partial PI-CB, full CBs and CE&AO methods versus different number of RIS elements in SU and MU scenarios.

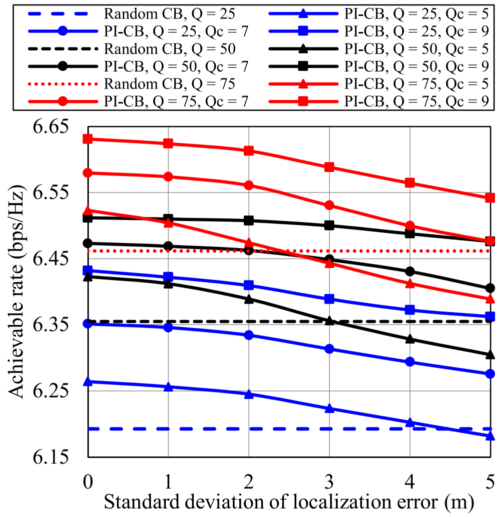


FIGURE 12. The achievable rate of the proposed partial PI-CB scheme versus localization accuracy.

In contrast, the complexity of RP selection using the proposed CB, or any other CB based scheme, is $\mathcal{O}(QNK^3)$, which is extremely lower comparable to that of AO method, and it is independent of number of RIS elements and is only a function of CB size. Furthermore, using partial PI-CB with number of candidate RPs further reduces the RPs selection complexity.

Hence, a wise selection of Q and Q_c, considering the channel coherence time, can guarantee balancing between the obtained rate and system complexity. Fig. 11 shows the complexity order of reflection pattern determination if the system uses the proposed partial CB, full CBs whether randomly generated or proposed one and AO methods versus number of RIS elements in SU and MU cases assuming $Q = 25$. Moreover, we consider $N_i = 1$, which is a simplified assumptions, because in practical N_i is larger than 1. It is clear

that CE&AO scheme is more complicated, e.g., in 4 UEs case with 80 RIS elements, it needs more than a 14×10^3-times operations to optimize the RIS reflection pattern. Furthermore, the partial PI-CB decreases the complexity to 63%, 48% and 42.2% of the complexity needed using the full CBs.

There is another factor that affects the best number of candidate RPs that should be chosen which is the positioning error, because UEs positions come with a localization error. Consequently, we discuss in this paragraph the impact of this error on the performance of the partial PI-CB scheme. Fig. 12 presents the achievable rate of the proposed scheme versus localization accuracy and compares it with the random CB performance, which is considered the margin, in SU case. Also, we consider the standard deviation of the error between 0 and 5m, as many positioning services can provide UE location within this range, e.g., Wi-Fi has a 2.5m error on average in outdoor areas. Moreover, we study the cases where the numbers of the selected candidate RPs are 5, 7, and 9, assuming different CB sizes, 25, 50, and 75. The degradation in localization accuracy slightly decreases the achievable rate of the proposed partial PI-CB scheme, especially if a higher number of candidate RPs is used to find the best codeword for RIS configuration. For example, if the error increases from 0 to 5m, the proposed scheme achievable rate, when $Q = 25$ and $Q_c = 5$, will only decrease by 0.08 bps/Hz, and it will still higher than the rate obtained by random CB. Moreover, using more candidate codewords can eliminate this effect to guarantee obtaining a rate higher than that obtained by random CB. For instance, when $Q = 50$ and using 7 or 9 candidate RPs, the proposed scheme can guarantee 6.40 and 6.47 bps/Hz achievable rate, respectively, though the positioning accuracy dropped to 5m. Moreover, these rates are 0.05 and 0.12 bps/Hz higher than that achieved by random CB with the same size, respectively. To sum up, selecting the optimal number of candidate RPs, in our partial PI-CB proposal is 9, can guarantee a higher immunity against localization error, hence obtaining better performance with extremely low complexity and overhead compared to the CE&AO and random CB schemes even if positioning information is not 100% accurate.

VII. CONCLUSION

In this work, we propose a new PI-CB for RIS passive beamforming in single user and multiuser MISO systems. This CB is designed online, so it can efficiently represent the area of interest. Additionally, as the PI-CB stores corresponding UEs PI for each designed RP, further reduction in the system overhead and complexity can be achieved by only training a group of chosen RPs instead of the full CB. The design of this partial PI-CB is done based on the distance metric between the new UEs PI and the stored PI in the full PI-CB. We proved that the proposed full and partial PI-CB can achieve high performance with much lower overhead and complexity than CE&AO and random CB schemes even if different scenarios are adopted. In addition, considering time-variant channels, the two proposed PI-CBs obtain a higher effective rate than other schemes, particularly in rapidly changing channels in single user scenario, and in all cases in multiuser scenarios. Moreover, we evaluate our PI-CBs versus the increase of the number of RIS elements, where our proposals achieve higher and stable effective rates comparable to optimization based scheme. Finally, we studied the impact of the positioning error on the proposed partial PI-CB scheme performance and found that a slight reduction occurs due to this error because the stored information also has this positioning error. Hence, we discovered that using 9 candidate RPs in the searching group is the best number of RPs because a balance between performance, overhead, complexity, and positioning error effect can be obtained. In the future, we will study a more dynamic PI-CBs, that can be updated based on the environmental changes and UEs mobility. Moreover, device to device scenario, where both the TX and the RX are moving, is still an open direction. Furthermore, investigations on how the PI can assist in deep learning based RIS passive beamforming may be another contribution.

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