Precoder Design in User-Centric Virtual Cell Networks

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***Abstract*—We consider the coordinated transmission in the downlink of user-centric virtual cell networks where a number of Remote Radio Heads (RRHs) form a *virtual cell* to serve every user equipment (UE). We introduce two cell formation schemes and design the precoders in order to optimize the sum data rate with fairness among users. The original non-convex weighted sum-rate maximization problem is converted into an equivalent matrix-weighted sum- mean square error (MSE) minimization problem, which is solved by a distributed precoding algorithm. Simulation results show that the proposed weighted minimum mean square error (WMMSE) algorithm provides a substantial gain over existing algorithms in terms of sum data rates with moderate implementation cost.**

I. Introduction

The next generation wireless communication systems such as 5G will have to provide a thousand times more data traffic than it has to today [1]. To meet the requirement, user-centric virtual cell networks have been identified in [2] as one of five key disruptive technologies for 5G, which can offer ubiquitous user experience and make dramatic improvements in both spectral and energy efficiency. In the network, a number of distributed Remote Radio Heads (RRHs) are connected to a central controller via high-bandwidth low-latency optics.

Many similar works exist in multi-cell cooperation networks and distributed antenna systems (DAS). In cooperative multi-cell networks, a novel precoding scheme is proposed in [3] for base station cooperation in the downlink which considered overlapped clusters. In [4], the authors propose a scheme for both multi-cell and mixed macrocell and femtocell/picocell network to optimize jointly the user schedule, transmit and receive precoding vectors and the transmit power spectra. In DAS, authors in [5] derive the optimal precoder in a closed form. In [6], the authors propose a transmit covariance optimization method to maximize the energy efficiency for a single-user DAS.

In contrast to user-centric virtual cell networks, these related works either ignore how to choose the optimal base station set or only concern a single-user systems which indicates that there is no inter-user interference and make the optimization problem simple and tractable. The cell formation schemes in virtual cell networks are completely different, since each user can choose its serving RRH set to form a virtual cell [7]. In this way, there is no cell edge any more, and the performance of each user can be greatly improved by deploying more RRHs into each virtual cell.

The cell formation scheme and downlink precoding technology are the vital parts in virtual cell networks. The former determines a set of RRHs that will serve the same UEs, while the latter one effectively eliminates the inter-user interference, both can significantly improve user experience. However, to the best of the authors knowledge, few existing papers focus on cell formation schemes. Regarding downlink precoding, a new formulation of the beamforming problem is developed in [8] for sum-rate maximization and the structure of its optimal solution is analyzed.

In this paper, we take both cell formation schemes and precoder design into consideration and solve the two problems separately. Firstly, we introduce two virtual cell formation methods with different setting of cell size in user-centric virtual cell networks. Secondly, in order to solve the precoding problem, we formulate the popular weighted sum-rate maximization problem and prove that it is equivalent to a matrix-weighted sum mean square error (S-MSE) minimization problem. Then we develop a distributed weighted minimum mean square error (WMMSE) precoding algorithm for the user-centric virtual cell networks, the performance of which is validated by numerical results.

The rest of this paper is organized as follows. In Section II, we present the system model and two cell formation methods are introduced. In section III, we propose the distributed WMMSE precoding algorithm. Numerical results are given in Section IV and conclusions are drawn in Section V.

Notation: Uppercase and lowercase boldface denote matrices and vectors, respectively. For a matrix $\mathbf{A}$, $[\mathbf{A}]_{i,:}$ and $[\mathbf{A}]_{i,j}$ mean the i-th row of $\mathbf{A}$ and the (i,j)-th element of $\mathbf{A}$, respectively. $(\cdot)^{\mathrm{T}}$, $(\cdot)^{\mathrm{H}}$ and $\mathrm{tr}(\cdot)$ denote transpose, Hermitian transpose and trace operator, respectively. Expectation is denoted by $\mathbb{E}[\cdot]$; $\|\mathbf{A}\|_{\mathrm{F}}$ and $|\mathbf{A}|$ (or $\det(\cdot)$) are the Frobenius norm of $\mathbf{A}$ and its determinant. $\mathbf{I}_N$ is the $N \times N$ identity matrix; $\mathcal{CN}(\mathbf{a}, \mathbf{A})$ is a complex Gaussian vector with mean $\mathbf{a}$ and covariance matrix $\mathbf{A}$.

II. System Model and Cell Formation

In this section, we introduce the system model considered in this paper as well as the methods used for virtual cell formation.

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A. System model

We consider the downlink of a virtual cell network with universal frequency reuse and all the users are scheduled at the same time. The virtual cell network consists of a set of M RRHs denoted as $\mathcal{M}$ and a set of K UEs denoted as $\mathcal{K}$, such that $|\mathcal{M}| = M$, $|\mathcal{K}| = K$, where operation $|\cdot|$ represents the cardinal number of a set. Each RRH and UE are equipped with N_T and N_R antennas, respectively.

The set of RRHs serving a specific UE is defined as a virtual cell. Denote $\mathcal{M}_k \subseteq \mathcal{M}$ and $\mathcal{K}_m \subseteq \mathcal{K}$ as the active RRH cluster for UE k and the set of UEs whose virtual cell is formed by RRH m, respectively. Note that the remaining unselected RRHs can be turned off to reduce the power consumption. For the user-centric networks, multiple UEs have diverse rate requirements and channel conditions, which inevitably leads to overlapped virtual cells, i.e., $\forall k, k' \in \mathcal{K}$ and $k \neq k'$, $\mathcal{M}_k \cap \mathcal{M}_{k'} \neq \emptyset$. In the rest of paper, we denote $|\mathcal{M}_k| = M_k, \forall k \in \mathcal{K}$ and the total number of transmit antennas for UE k as N_T^k.

The channel matrix from RRH m to UE k is denoted by $\mathbf{H}_{m,k} \in \mathbb{C}^{N_R \times N_T}$, the i-th row of which is given by

$$[\mathbf{H}_{m,k}]_{i,:} = [\alpha_{mki,1}, \alpha_{mki,2}, \cdots, \alpha_{mki,N_T}]\sqrt{\rho_{mk}},$$

where $\alpha_{mki,n} \in \mathcal{CN}(0,1), n = 1, 2, \ldots, N_T$ is the Rayleigh fading channel coefficient and ρ_{mk} is a large-scale fading (e.g., path loss and shadowing) from RRH m to UE k.

The received signal at UE k is given by

$$\mathbf{y}_k = \mathbf{H}_{k\text{-}k}\mathbf{F}_k\mathbf{x}_k + \sum_{j \neq k, j \in \mathcal{K}} \mathbf{H}_{j\text{-}k}\mathbf{F}_j\mathbf{x}_j + \mathbf{n}_k. \tag{1}$$

where $\mathbf{x}_k \in \mathbb{C}^{N_s}$ is the transmitted symbol vector of UE k with zero-mean and $\mathbb{E}[\mathbf{x}_k\mathbf{x}_k^{\mathrm{H}}] = \frac{1}{N_s}\mathbf{I}_{N_s}$.

$$\begin{aligned}\mathbf{H}_{j\text{-}k} &= [\mathbf{H}_{m_1,k}, \mathbf{H}_{m_2,k}, \cdots, \mathbf{H}_{m_{M_j},k}] \in \mathbb{C}^{N_R \times N_T^j},\\ \mathbf{F}_j &= [\mathbf{F}_{m_1,j}^{\mathrm{T}}, \mathbf{F}_{m_2,j}^{\mathrm{T}}, \cdots, \mathbf{F}_{m_{M_j},j}^{\mathrm{T}}]^{\mathrm{T}} \in \mathbb{C}^{N_T^j \times N_s},\end{aligned} \tag{2}$$

where $m_i \in \mathcal{M}_j$. $\mathbf{F}_{m,k} \in \mathbb{C}^{N_T \times N_s}$ is the precoding matrix for user k at RRH m; $\mathbf{n}_k \in \mathbb{C}^{N_R \times 1}$ is the additive white Gaussian noise with zero-mean and covariance $\mathbb{E}[\mathbf{n}_k\mathbf{n}_k^{\mathrm{H}}] = \sigma_k^2\mathbf{I}_{N_R}$. We assume that $\mathbf{x}_k$ and $\mathbf{x}_j$ ($\mathbf{n}_k$ and $\mathbf{n}_j$) are independent if $k \neq j$.

Then the data rate of UE k is

$$R_k = \log_2 \det(\mathbf{I}_{N_R} + \mathbf{\Gamma}_k), \tag{3}$$

where

$$\mathbf{\Gamma}_k = \mathbf{H}_{k\text{-}k}\mathbf{F}_k\mathbf{F}_k^{\mathrm{H}}\mathbf{H}_{k\text{-}k}^{\mathrm{H}}\mathbf{Z}_k^{-1},$$

and $\mathbf{Z}_k = \sum_{j \neq k, j \in \mathcal{K}} \mathbf{H}_{j\text{-}k}\mathbf{F}_j\mathbf{F}_j^{\mathrm{H}}\mathbf{H}_{j\text{-}k}^{\mathrm{H}} + N_s\sigma_k^2\mathbf{I}_{N_R}$.

In this paper, we adopt linear decoder at user terminals so that the post-processed signal is given by

$$\widehat{\mathbf{x}}_k = \mathbf{P}_k^{\mathrm{H}}\mathbf{y}_k,$$

where $\mathbf{P}_k \in \mathbb{C}^{N_R \times N_s}$ is decoding matrix for UE k.

The interest of this paper is to find the transmit and decoding matrix $\mathbf{F}_k$ and $\mathbf{P}_k$ such that a certain utility of the virtual cell networks (e.g., minimizing the sum MSE) is optimized with the following power constraint for each RRH is met:

$$\sum_{k \in \mathcal{K}_m} \mathrm{tr}(\mathbf{F}_{m,k}\mathbf{F}_{m,k}^{\mathrm{H}}) \leq P_{\max}, \forall m = 1, \cdots, M$$

where $P_{\max}$ is the maximum available power for each RRH. According to the structure of $\mathbf{F}_k$ in (2), we can relax the above power budget to

$$\mathrm{tr}(\mathbf{F}_k\mathbf{F}_k^{\mathrm{H}}) \leq M_k P_{\max}, \forall k = 1, \cdots, K \tag{4}$$

B. Virtual Cell Formation

The virtual cell is formed from a user's perspective. UE k feeds back the channel matrix of $|\mathcal{M}_k|$ RRHs with the strongest channel gains to form its serving RRH set $\mathcal{M}_k$. We define the size of virtual cell to be the number of RRHs which serve the user. Similar to [3] and motivated by [9], we introduce two forming approaches with different settings of cell size:

1) Maximum Gain Forming (MGF). The RRH set $\mathcal{M}_k$ for user k is formed by M_k RRHs with strongest channel gains. An example of a virtual cell scenario is given in Fig.1, where cell size is fixed to 3.
2) Threshold Forming (TF). This scheme depends on the relative channel gain, as summarized in **Table I**. The RRH set for user k can be expressed as

$$\mathcal{M}_k = \left\{ m \middle| \frac{\|\mathbf{H}_{m,k}\|_{\mathrm{F}}^2}{\max\{\|\mathbf{H}_{m',k}\|_{\mathrm{F}}^2\}_{m' \in \mathcal{M}}} \geq \beta_k, m \in \mathcal{M} \right\}, \tag{5}$$

where $0 < \beta_k \leq 1$ is the threshold of relative channel strength, which is defined as the ratio of the squared Frobenius norm of $\mathbf{H}_{m,k}$ to that of the strongest channel. Obviously, it is of great importance to choose an appropriate threshold β_k for system performance and interference elimination. Specifically, if β_k is too small, it will result in large cell size for UE k which requires more RRHs to cooperate with each other leading to high signaling overhead and severe inter-cell interference to other UEs. On the other hand, when β_k is too large, there may be only one RRH serving this UE (i.e., no RRH coordination).

In Fig.1, it is reasonable that some user equipments should not choose the nearest three RRHs for cooperative communication, because of different shadow fading and path loss.

For TF scheme, the RRHs with strongest channels is variable for each user because the channel is random. Moreover, the cell size may change dynamically according to threshold β_k. Therefore, TF may achieve results different from MGF. The computational complexity of TF scheme in Table I is dominated by searching the maximum. Thus, the complexity is $\mathcal{O}(KM)$.

It is hard to acquire an appropriate threshold β_k, because of non-closed expression of β_k. To solve the threshold choice problem and obtain a near-optimal threshold $\boldsymbol{\beta} = \{\beta_1, \cdots, \beta_K\}$, we formulate it into a performance maximization problem and propose a simple yet effective method called

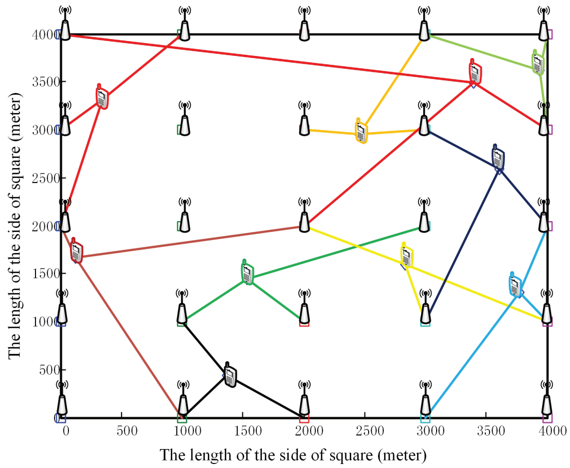

Fig. 1. A snapshot of link geometry for User-Centric Virtual Cell Network. The line represents that the communication connection between UE and RRH, and different colors indicate different virtual cells. 25 RRHs and 10 UEs are distributed in the square region. The virtual cell formulation scheme is MGF, where $|\mathcal{M}_k| = M_k = 3$.

TABLE I
TF SCHEME

STEPS	OPERATIONS
1	Generate channel matrix $\mathbf{H}_{m,k}(m \in \mathcal{M}, k \in \mathcal{K})$ according to their locations;
2	**For** each UE$(k \in \mathcal{K})$ Val = arg $\max_{m \in \mathcal{M}}\{\|\mathbf{H}_{m,k}\|_{\mathrm{H}}^2\}$; $\mathcal{M}_k = \emptyset$; **While** $\|\mathbf{H}_{m*,k}\|_{\mathrm{F}}^2/\text{Val} \geq \beta_k$, $m* \in \mathcal{M}$ Let $\mathcal{M} = \mathcal{M}\backslash\{m*\}$, $\mathcal{M}_k = \mathcal{M}_k \bigcup\{m*\}$; **End** **End**

K-dimensional grid search, which will be introduced in future work. Obviously, the K-dimensional grid search can be very complex for large values of K.

III. Precoding for Weighted Sum Rate Maximization

In this section, we devise a precoding scheme in order to maximize the weighted sum-rate assuming MGF scheme is used for virtual cell formation. We set up a weighted sum-rate maximization problem and design the precoders by converting the original problem to an equivalent matrix-weighted S-MSE minimization problem.

Let $\mathbf{F} \triangleq \{\mathbf{F}_k|k \in \mathcal{K}\}$, and then the weighted sum rate maximization problem can be formulated as

$$\mathbf{F}^* = \arg\max_{\mathbf{F}} \sum_{k=1}^{K} \alpha_k R_k \quad \text{s.t. } (4) \tag{6}$$

in which the weight α_k represents the priority of UE k in the whole network and R_k is the data rate of UE k which is given in (3).

Obviously, the optimization problem of (6) is non-convex and thus difficult to find the global optimal solution. Therefore, we need to convert it to an equivalent form which is tractable.

A. *Equivalent Matrix-weighted Sum-MSE Minimization Problem*

In order to solve (6), let us first examine the MSE matrix $\mathbf{E}_k$ for UE k, which is given by

$$\begin{aligned}\mathbf{E}_k &= \mathbb{E}_{\mathbf{x},\mathbf{n}}\left[(\widehat{\mathbf{x}}_k - \mathbf{x}_k)(\widehat{\mathbf{x}}_k - \mathbf{x}_k)^{\mathrm{H}}\right]\\ &= \frac{1}{N_s}(\mathbf{I} - \mathbf{P}_k^{\mathrm{H}}\mathbf{H}_{k\text{-}k}\mathbf{F}_k)(\mathbf{I} - \mathbf{P}_k^{\mathrm{H}}\mathbf{H}_{k\text{-}k}\mathbf{F}_k)^{\mathrm{H}}\\ &+ \frac{1}{N_s}\sum_{j\neq k, j\in\mathcal{K}} \mathbf{P}_k^{\mathrm{H}}\mathbf{H}_{j\text{-}k}\mathbf{F}_j\mathbf{F}_j^{\mathrm{H}}\mathbf{H}_{j\text{-}k}^{\mathrm{H}}\mathbf{P}_k + \sigma_k^2\mathbf{P}_k^{\mathrm{H}}\mathbf{P}_k,\end{aligned} \tag{7}$$

where the expectation is taken over $\mathbf{x}$ and $\mathbf{n}$. Then the S-MSE minimization problem can be formulated as

$$\{\mathbf{F}^*, \mathbf{P}^*\} = \arg\min_{\mathbf{F},\mathbf{P}} \sum_{k=1}^{K} \text{tr}(\mathbf{E}_k) \quad \text{s.t. } (4), \tag{8}$$

where $\mathbf{P} \triangleq \{\mathbf{P}_k|k \in \mathcal{K}\}$ is the combined decoding matrix.

Given $\mathbf{F}$, the minimization problem (8) leads to a MMSE receiver, i.e., $\partial\text{tr}(\mathbf{E}_k)/\partial\mathbf{P}_k = \mathbf{0}$, which gives

$$\mathbf{P}_k^{\text{mmse}} = \mathbf{U}_k^{-1}\mathbf{H}_{k\text{-}k}\mathbf{F}_k, \tag{9}$$

where $\mathbf{U}_k = \sum_{j\in\mathcal{K}} \mathbf{H}_{j\text{-}k}\mathbf{F}_j\mathbf{F}_j^{\mathrm{H}}\mathbf{H}_{j\text{-}k}^{\mathrm{H}} + N_s\sigma_k^2\mathbf{I}_{N_R}$ is the co-variance matrix of the total received signal and additive noise at UE k. Using the above MMSE receiver, the corresponding MSE matrix can be deduced to

$$\begin{aligned}\mathbf{E}_k^{\text{mmse}} &\overset{(a)}{=} \mathbb{E}_{\mathbf{x},\mathbf{n}}\left[-(\widehat{\mathbf{x}}_k - \mathbf{x}_k)\mathbf{x}_k^{\mathrm{H}}\right]\\ &= \frac{1}{N_s}\left(\mathbf{I} - \mathbf{F}_k^{\mathrm{H}}\mathbf{H}_{k\text{-}k}^{\mathrm{H}}\mathbf{U}_k^{-1}\mathbf{H}_{k\text{-}k}\mathbf{F}_k\right),\end{aligned} \tag{10}$$

where (a) follows from independence between the detection error and detection result of MMSE.

To this end, we are able to convert the original sum-rate maximization problem (6) to the following matrix-weighted S-MSE minimization problem:

$$\min_{\mathbf{F},\mathbf{P},\mathbf{W}} \sum_{k=1}^{K} \alpha_k\Big(\text{tr}(N_s\mathbf{W}_k\mathbf{E}_k) - \text{logdet}(\mathbf{W}_k)\Big) \quad \text{s.t. } (4) \tag{11}$$

where $\mathbf{W}_k \succeq 0$ is a weight matrix for UE k and $\mathbf{W} \triangleq \{\mathbf{W}_k|k \in \mathcal{K}\}$.

Proposition 1: Problem (11) is equivalent to (6).

Proof: It is obvious that $\mathbf{P}_k^{\text{mmse}}$ in formula (9) is the optimal solution of problem (11). Let $f(\mathbf{F}_k, \mathbf{P}_k, \mathbf{W}_k)$ be the objective function in problem (11). Then, f is con-vex w.r.t. $\mathbf{W}_k$ when all the other variables are fixed. By checking the first order optimality condition for $\mathbf{W}_k$, i.e., $\partial f(\mathbf{F}_k, \mathbf{P}_k, \mathbf{W}_k)/\mathbf{W}_k = 0$, we obtain $\mathbf{W}_k^{\text{opt}} = (N_s\mathbf{E}_k)^{-1}$. Substituting optimal $\mathbf{P}_k$ and $\mathbf{W}_k$ into (11) gives

$$\max_{\mathbf{F}} \sum_{k=1}^{K} \alpha_k\text{logdet}\big((N_s\mathbf{E}_k^{\text{mmse}})^{-1}\big) \quad \text{s.t. } (4) \tag{12}$$

Next, we only need to prove that $\text{logdet}\big((N_s\mathbf{E}_k^{\text{mmse}})^{-1}\big) = R_k$.

$$\begin{aligned}\text{logdet}\big((N_s\mathbf{E}_k^{\text{mmse}})^{-1}\big) &\overset{(a)}{=} \text{logdet}\big(\mathbf{I}-\mathbf{F}_k^{\text{H}}\mathbf{H}_{k\text{-}k}^{\text{H}}\mathbf{U}_k^{-1}\mathbf{H}_{k\text{-}k}\mathbf{F}_k\big)\\ &\overset{(b)}{=} \text{logdet}\big(\mathbf{I}+\mathbf{F}_k^{\text{H}}\mathbf{H}_{k\text{-}k}^{\text{H}}\mathbf{Z}_k^{-1}\mathbf{H}_{k\text{-}k}\mathbf{F}_k\big)\\ &\overset{(c)}{=} \text{logdet}\big(\mathbf{I}+\mathbf{H}_{k\text{-}k}\mathbf{F}_k\mathbf{F}_k^{\text{H}}\mathbf{H}_{k\text{-}k}^{\text{H}}\mathbf{Z}_k^{-1}\big)\\ &= R_k\end{aligned}$$

where (a) and (b) are achieved from (10) and using the Woodbury matrix identity, respectively. Here $\mathbf{Z}_k$ is given in (3) and (c) follows the fact that $\det(\mathbf{I}+\mathbf{AB}) = \det(\mathbf{I}+\mathbf{BA})$. ■

Proposition 1 shows that maximizing sum-rate utility can be solved via matrix-weighted S-MSE minimization. Although the latter problem has more variables, it is tractable since the objective is convex on each variable.

B. Distributed WMMSE Algorithm

In this subsection, we introduce a weighted mean square error (WMMSE) algorithm [10] for matrix-weighted S-MSE minimization problem. To solve problem (11), the block coordinate descent method is used. Specifically, we minimize the objective by iteratively update one variable while fixing two other variables.

Denote $\mathbf{F}^{(n)}$, $\mathbf{W}^{(n)}$ and $\mathbf{P}^{(n)}$ as the outputs of the n-th iteration. Then $\mathbf{P}_k^{(n+1)}$, $\mathbf{F}_k^{n+1}$and $\mathbf{W}_k^{n+1}$ are computed for each user k in a distributed way.

$\mathbf{P}_k^{(n+1)}$ is calculated according to the MMSE solution in (9). Regarding $\mathbf{W}_k^{n+1}$, we have proved in Proposition 1 that the optimal solution is

$$\mathbf{W}_k^{(n+1)} = (N_s\mathbf{E}_k)^{-1}, \tag{13}$$

where $\mathbf{E}_k$ is given in (7). To calculate $\mathbf{F}_k$, the problem (11) can be rewritten as

$$\begin{aligned}\min_{\mathbf{F}_k} \quad & A_k + B_k\\ \text{s.t.} \quad & \text{tr}(\mathbf{F}_k\mathbf{F}_k^{\text{H}}) \le M_k P_{\max}\end{aligned} \tag{14}$$

where

$$A_k = \text{tr}\big(\alpha_k\mathbf{W}_k(\mathbf{I}-\mathbf{P}_k^{\text{H}}\mathbf{H}_{k\text{-}k}\mathbf{F}_k)(\mathbf{I}-\mathbf{P}_k^{\text{H}}\mathbf{H}_{k\text{-}k}\mathbf{F}_k)^{\text{H}}\big),$$

$$B_k = \sum_{j\neq k, j\in\mathcal{K}} \text{tr}\big(\alpha_j\mathbf{W}_j\mathbf{P}_j^{\text{H}}\mathbf{H}_{j\text{-}k}\mathbf{F}_k\mathbf{F}_k^{\text{H}}\mathbf{H}_{j\text{-}k}^{\text{H}}\mathbf{P}_j\big).$$

The above problem is a convex quadratic optimization problem on $\mathbf{F}_k$, which can be solved by using standard convex programming tools.

From the implementation point of view, some reasonable assumptions were made to implement the distributed WMMSE algorithm [11]. We assume that local channel information can be available for each user, in other word, each RRH m knows the local channel matrix $\mathbf{H}_{m,k}$ to UE k. We also assume that each UE can feedback information (e.g., the updated decoding matrix $\mathbf{P}_k$) to the RRHs.

Specifically, the central controller predetermines the RRH set for each user, i.e., $\mathcal{M}_k, \forall k \in \mathcal{K}$ and the users served by RRH m, i.e., $\mathcal{K}_m$, and these information will be delivered to all users. Then, each user estimates the received signal covariance matrix $\mathbf{U}_k$ and calculate corresponding weight matrix $\mathbf{W}_k$ and decoding matrix $\mathbf{P}_k$. At last, users feed back these information to the RRHs which will be handled by central controller. Therefore, this algorithm runs distributedly for each virtual cell. It should also be noted that the maximum iteration number $N_{\max}$ should be large in order to reduce the power consumption of user equipments.

The WMMSE precoding algorithm for user-Centric virtual Cell Networks is summarized in **Algorithm 1**.

Algorithm 1 Distributed WMMSE Algorithm

1: The iteration number $n = 1$;
2: Initialize precoding matrix $\mathbf{F}_{m,k}^{(n)}, m \in \mathcal{M}_k, k \in \mathcal{K}$ such that $\text{tr}(\mathbf{F}_{m,k}^{(n)}(\mathbf{F}_{m,k}^{\text{H}}))^{(n)}) = P_m/K_m$, and form $\mathbf{F}_k^{(n)}$ according to (2);
3: **for** $k = 1, 2, \cdots, K$ **do**
4: $\quad \mathbf{W'}_k^{(n)} = \mathbf{W}_k^{(n)}$;
5: $\quad \mathbf{P}_k^{(n)} = (\mathbf{U}_k^{-1})^{(n)}\mathbf{H}_{k\text{-}k}^{(n)}\mathbf{F}_k^{(n)}$, according to (9);
6: $\quad \mathbf{W}_k^{(n)} = (N_s\mathbf{E}_k^{\text{mmse}})^{-1}$, according to (10) and (13);
7: $\quad$ Update $\mathbf{F}_k^{(n)}$, according to standard convex programming tools;
8: **end for**
9: If $\big|\sum_{k\in\mathcal{K}}\big(\text{logdet}(\mathbf{W}_k^{(n)}) - \text{logdet}(\mathbf{W'}_k^{(n)})\big)\big| < \epsilon$ or $n > N_{\max}$, terminate. Otherwise, set $n = n+1$ and go to step 2.

Due to the distributed manner, the proposed algorithm requires less signaling exchange within the network. According to a similar complexity analysis in [10], the complexity of the WMMSE algorithm is $\mathcal{O}(N_{\max}K^2N_TN_R^2 + N_{\max}K^2N_T^2N_R + N_{\max}K^2N_T^3 + N_{\max}KN_R^3)$. It is reasonable to assume that $N_T \gg N_R$ and the complexity is thus given by $\mathcal{O}(N_{\max}K^2N_T^3)$.

IV. Simulation Results

In the simulations, we use the topology shown in Fig.1, where the length of the square is 4000 meters and all RRHs are uniformly placed while the users are uniformly and randomly generated. Each RRH has 23 dBm power budget and 4 antennas, while each UE has only one antenna. For a fair comparison with [8], we adopt the same parameters by setting $N_s = 1$ and system bandwidth to be 5 MHz. The standard deviation of shadowing is 8 dB and the pass loss is given by $d^{-\alpha}$, where $\alpha = 3.76$ and d is the distance from RRH to UE in kilometer. We assume $\sigma_k^2 = -174$ dBm/Hz and the weight of each user is equal to 1. For algorithm implementation, we use $\epsilon = 10^{-5}$ and $N_{\max} = 2$ [10].

To evaluate the performance of WMMSE algorithm (**Algorithm 1**), we compare it with two existing algorithms:

- EigPre: Eigenprecoding with fixed power allocation [8].
- ZF: Zero-forcing precoding with total power constraints [12]–[14].

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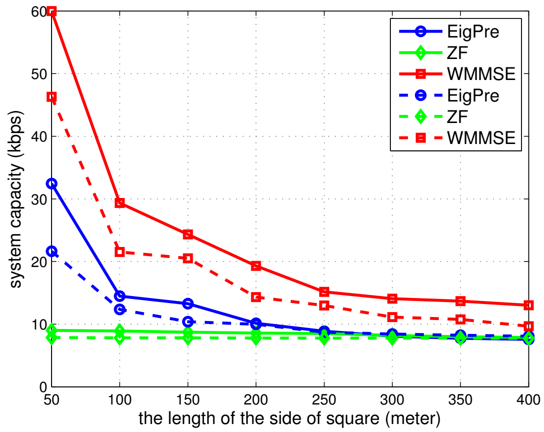

Fig. 2. System capacity comparison of different precoding algorithms. Soild lines represent the virtual cell size is 2, while dashed lines mean virtual cell size is 1 (i.e., no RRH coordination).

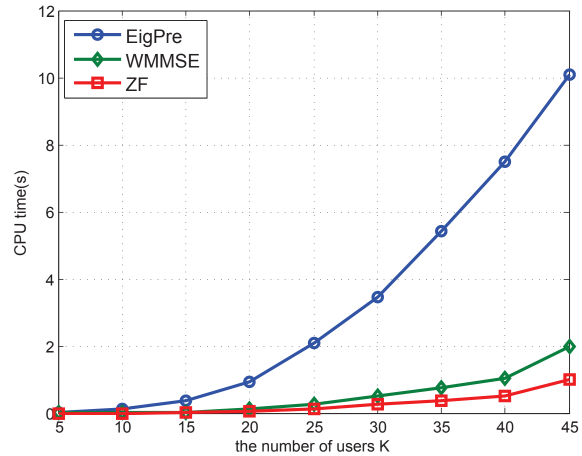

Fig. 3. Implementation CPU time versus the number of users in the whole system, where the maximum iteration number and cell size are both 2.

Fig.2 shows the comparison between WMMSE and EigPre, ZF in terms of system capacity. It can be seen that the WMMSE algorithm achieves much higher capacity than the two existing algorithms under different virtual cell size. In addition, the performance of EigPre and ZF increase marginally with virtual cell size, while the WMMSE algorithm shows a substantial gain. This result shows that merely adopting RRH coordination in virtual cell without delicate precoding algorithms may not improve the system performance. It also should be noted that when the size of the area becomes large, increasing cell size (i.e., RRH coordination) can barely improve system capacity.

In Fig.3, we compare the implementation time with the two existing algorithms. The simulations were operated in MATLAB R2014a on a computer with 3.2 GHz Intel Core i5 processor. Although the CPU time not totally represents the actual computation speed, it can be a metric for performance comparison. It can be observed that the WMMSE algorithm significantly outperform EigPre algorithm especially when the number of users is large and slightly inferior to ZF algorithm.

V. Conclusion

In this paper, we study the precoding problem for maximizing weighted sum-rate in user-centric virtual cell networks, and introduce two virtual cell formation methods with different setting of cell size. We reformulate the popular weighted sum-rate maximization problem into an equivalent matrix-weighted sum-MSE minimization problem, based on which we solved the precoding problem and developed a distributed WMMSE algorithm. Simulation results show that the WMMSE algorithm outperforms the two existing algorithms in terms of system capacity and the implementation time is modest in various system environments.

Acknowledgments

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