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USER SCHEDULING USING GRAPH NEURAL NETWORKS FOR RECONFIGURABLE INTELLIGENT SURFACE ASSISTED MULTIUSER DOWNLINK COMMUNICATIONS

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ABSTRACT

Reconfigurable intelligent surface (RIS) is capable of intelligently manipulating the phases of the incident electromagnetic wave to improve the wireless propagation environment between the base station (BS) and the users. This paper addresses the joint user scheduling, RIS configuration, and BS beamforming problem in an RIS-assisted downlink network with limited pilot overhead. We show that graph neural networks (GNN) with permutation invariance and equivariance properties can be used to appropriately schedule users and to design RIS configurations to achieve high overall throughput while accounting for fairness among the users. As compared to the conventional methodology of first estimating the channels then optimizing the user schedule, RIS configuration and the beamformers, this paper shows that an optimized user schedule can be obtained directly from a very short set of pilots using a GNN, then the RIS configuration can be optimized using a second GNN, and finally BS beamformers can be designed based on the overall effective channel. Numerical results show that the proposed approach can utilize received pilots more efficiently than conventional channel estimation based approach.

1. INTRODUCTION

Reconfigurable intelligent surface (RIS) is envisioned as a key enabling technology for a smarter radio environment [1]–[5], due to its capability to manipulate the phases of wireless signals to enhance the transmission environment and to improve the network utility (e.g., sum-rate [6] or minimum rate [7]). This paper addresses a key problem of user scheduling for the RIS-assisted wireless cellular network. In a downlink transmission environment with a base-station (BS) equipped with M antennas, which can serve at most M users simultaneously over the same resource block, if the total number of users in the network K is greater than M, how should the BS optimally schedule a subset of users at each timeslot in conjunction with the optimal RIS configuration and the BS beamforming to achieve high network throughput while ensuring fairness across the users?

The traditional approach to user scheduling follows a two-step approach that aims to accurately recover the channel state information (CSI) in the first stage, then to optimize the downlink scheduling in the second stage. However, an RIS typically consists of a large number of passive elements, resulting in a large number of channel coefficients to estimate, and consequently a large pilot training overhead. In addition, the traditional channel estimation process typically uses a distance metric such as the mean squared error, which may not align with the network objective. Finally, even if the CSI is known perfectly, the user achievable rates are nonconvex functions of the RIS configuration and BS beamformers; further, the scheduling problem is a mixed discrete and continuous optimization problem, for which finding an optimal solution is computationally intensive for real-time applications.

To address this key challenge of CSI acquisition and network optimization, data-driven approaches have been proposed in recent literature. In [8]–[10], it is shown that deep neural networks can optimize the network utility directly based on received pilots. For example, [8] proposes a deep neural network to design analog beamformer given received pilots, which outperforms the conventional phase matching method based on the estimated CSI. In an RIS-assisted network, by leveraging deep learning approach, [9], [10] show that mapping the received pilots to the RIS configuration and BS beamforming can significantly reduce the pilot training overhead. However, most of the existing literature does not yet deal with the discrete optimization problem of scheduling, which is an important but challenging part of the overall network optimization.

This paper focuses on the scheduling aspect of an RIS-assisted multiuser downlink network. Toward this end, we make use of graph neural networks (GNN) just as in [10], but perform system-level optimization in three stages. Specifically, we show that in the first stage, a GNN applied to all potential users but with very short pilots can already produce an optimized schedule while accounting for the user priorities. In the second stage, a second GNN applied only to the scheduled users but with longer pilots are used to design the RIS configurations. In the final stage, the overall low-dimensional effective channels with the optimized RIS configuration are re-estimated in order to design the BS beamformers. Numerical results show that the proposed algorithm can learn to maximize the network utility with significantly reduced pilot overhead as compared to the conventional channel estimation based approach.

2. SYSTEM MODEL AND PROBLEM FORMULATION

2.1. System Model

Consider a downlink RIS-assisted multiuser MISO network, in which a BS equipped with M antennas serves K single-antenna users. An RIS with N passive elements is placed between the BS and the users to enhance the SINR of the received signals at the users. The RIS reflection coefficients are denoted as $\boldsymbol{\theta} = [e^{j\delta_1}, e^{j\delta_2}, \cdots, e^{j\delta_N}]^T \in \mathbb{C}^N$ with $\delta_n \in [0, 2\pi)$ denoting the phase shift of the n-th element, which can be independently controlled. We consider a scenario in which $K > M$, and the BS needs to schedule a subset of users at each timeslot. Let $\boldsymbol{\beta}^t = [\beta_1^t, \cdots, \beta_K^t]^\top \in \mathbb{C}^K$ denote the scheduling decision at the timeslot t, where $\beta_k^t = 1$ if the user k is scheduled, otherwise $\beta_k^t = 0$. Further, let $\boldsymbol{w}_k^t \in \mathbb{C}^M$ be the associated BS beamforming vector of the user k at the

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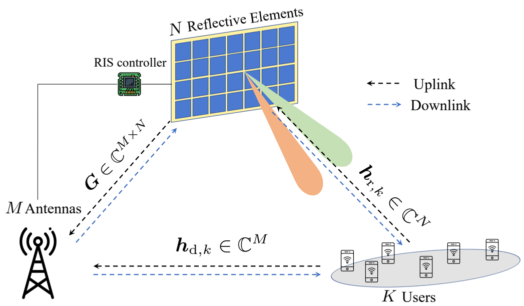


Fig. 1: RIS-assisted multiuser network.

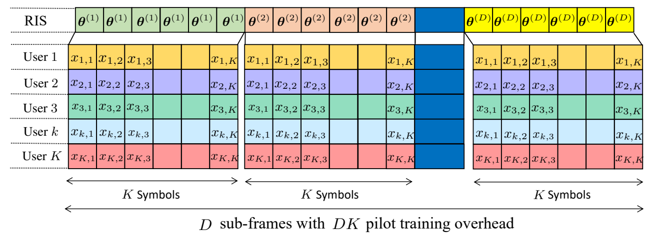


Fig. 2: Uplink pilot frame structure.

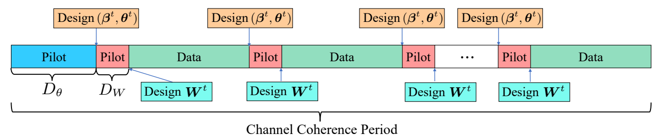


Fig. 3: Pilot placement over a coherence period.

t-th scheduling timeslot, so that $\|\boldsymbol{w}_k^t\|_2^2 = 0$ if $\beta_k^t = 0$, otherwise $\|\boldsymbol{w}_k^t\|_2^2 > 0$. We denote the BS beamforming matrix as $\boldsymbol{W}^t = [\boldsymbol{w}_1^t, \cdots, \boldsymbol{w}_K^t] \in \mathbb{C}^{M\times K}$.

The channel model is as shown in Fig. 1. The vector $\boldsymbol{h}_{\mathrm{d},k} \in \mathbb{C}^M$ denotes the direct link channel from the BS to the user k, and $\boldsymbol{h}_{\mathrm{r},k} \in \mathbb{C}^N$ and $\boldsymbol{G} \in \mathbb{C}^{M\times N}$ denote the channels between the RIS and the user k and between the BS and the RIS, respectively. The channels are assumed to be fixed across multiple scheduling timeslots. Let s_i^t denote the information symbol of user i. The received signal at the k-th user at the t-th scheduling timeslot is given by

$$r_k^t = \left(\boldsymbol{h}_{\mathrm{d},k} + \boldsymbol{A}_k\boldsymbol{\theta}^t\right)^\top \sum_{i=1}^{K} \boldsymbol{w}_i^t \beta_i^t s_i^t + n_k, \tag{1}$$

where $\boldsymbol{A}_k \triangleq \boldsymbol{G}\mathrm{diag}(\boldsymbol{h}_{\mathrm{r},k}) \in \mathbb{C}^{M\times N}$ is the cascade channel between the BS and the user k through the reflection at the RIS, $\boldsymbol{\theta}^t$ is the RIS reflection coefficients at the t-th scheduling timeslot, and $n_k \sim \mathcal{CN}(0, \sigma_0^2)$ is the additive noise. The achievable rate of the user k at the t-th scheduling timeslot can then be expressed as:

$$R_k^t = \log\left(1 + \frac{|(\boldsymbol{h}_{\mathrm{d},k} + \boldsymbol{A}_k\boldsymbol{\theta}^t)^\top \boldsymbol{w}_k^t|^2 \beta_k^t}{\sum_{i\neq k} |(\boldsymbol{h}_{\mathrm{d},k} + \boldsymbol{A}_k\boldsymbol{\theta}^t)^\top \boldsymbol{w}_i^t|^2 \beta_i^t + \sigma_0^2}\right). \tag{2}$$

The goal of this paper is to jointly optimize the scheduling decision, beamforming matrix, and reflection coefficients to maximize some utility function of R_k^t's. Thus, it is necessary to acquire some knowledge about the channel. In this paper, we assume channel reciprocity and that the system operates in time-division duplex (TDD) mode, so we rely on uplink pilot training to obtain the downlink CSI.

In particular, we adopt the pilots and the uplink RIS reflection coefficients design in [11], in which the training slots are equally partitioned to D sub-frames. Fig. 2 shows the frame structure of such an uplink pilot scheme in which the RIS reflection coefficients are randomly adjusted from sub-frame to sub-frame and remain fixed for each sub-frame, while the users repeatedly transmit the same mutually orthogonal pilot sequences of length K in each sub-frame, denoted as $\boldsymbol{x}_k$'s, where $\boldsymbol{x}_k^{\mathsf{H}} = [x_{k,1}, x_{k,2}, \cdots, x_{k,K}]$. Let $\boldsymbol{\theta}^{(d)}$ be the uplink RIS configuration in the d-th sub-frame. The received pilots in the d-th sub-frame $\boldsymbol{Y}^{(d)} \in \mathbb{C}^{M\times K}$ can be denoted as

$$\boldsymbol{Y}^{(d)} = \sum_{k=1}^{K} \left(\boldsymbol{h}_{\mathrm{d},k} + \boldsymbol{A}_k\boldsymbol{\theta}^{(d)}\right) \boldsymbol{x}_k^{\mathsf{H}} + \boldsymbol{N}^{(d)}, d = 1, ..., D. \tag{3}$$

By the orthogonality of the pilots, the contribution from the user k can be obtained as follows:

$$\boldsymbol{y}_k^{(d)} = \boldsymbol{Y}^{(d)}\boldsymbol{x}_k/K. \tag{4}$$

Collecting $\boldsymbol{y}_k^{(d)}$'s over D sub-frames gives $\tilde{\boldsymbol{Y}}_k^D = [\boldsymbol{y}_k^{(1)}, \cdots, \boldsymbol{y}_k^{(D)}]$. The overall pilot training overhead over D sub-frames is DK.

2.2. Proportional Fairness Scheduling

To ensure fairness, we define a network utility function over the long-term average rate achieved by each user according to an exponentially weighted moving average:

$$\bar{R}_k^t = (1-\gamma)\bar{R}_k^{t-1} + \gamma R_k^{t-1}, \tag{5}$$

where $0 \leq \gamma \leq 1$ is the forgetting factor. For proportional fairness scheduling, we use log-utility and solve a weighted sum-rate maximization problem

$$\sum_{k=1}^{K} \alpha_k^t R_k^t, \tag{6}$$

where the weights are set as $\alpha_k^t = 1/\bar{R}_k^t$, i.e., the inverse of the average rate prior to the t-th scheduling timeslot.

The system-level optimization process amounts to mapping the received pilots and the user weights to the schedule, RIS configuration, and the beamforming variables. Conceptually, the optimization problem in each scheduling slot can be thought of as:

$$\begin{aligned} \underset{\substack{(\boldsymbol{\beta}^t, \boldsymbol{W}^t, \boldsymbol{\theta}^t) = \\ f(\{\boldsymbol{Y}^{(d)}\}_{d=1}^D, \boldsymbol{\alpha}^t)}}{\text{maximize}} \quad & \sum_k \alpha_k^t R_k^t \\ \text{subject to} \quad & \sum_k \|\boldsymbol{w}_k^t\|^2 \leq P_d, \; |[\boldsymbol{\theta}^t]_n| = 1, \; \forall n, \\ & \sum_k \beta_k^t \leq M, \beta_k^t \in \{0, 1\}, \; \forall k, \end{aligned} \tag{7}$$

where $\boldsymbol{\alpha}_t = [\alpha_1^t, \cdots, \alpha_K^t]^\top$ and P_d is the downlink power constraint. Finding the optimal functional mapping $f(\cdot)$ in (7) is challenging, because (7) is a mixed discrete and continuous optimization problem with nonconvex objective. Moreover, the optimization variables are closely interrelated. For example, to minimize interference, we should schedule users whose channels are orthogonal, but to leverage the full benefit of RIS, the scheduled users should have channels that are closely correlated. In this paper, we utilize neural networks as powerful function approximators to model the mapping function $f(\cdot)$ and learn to balance these tradeoffs from data.

The training of such a neural network is however not easy, due to the large problem dimension. In the next section, we describe a pilot placement structure, as shown in Fig. 3, that allows such a mapping to be learned using two different GNNs over multiple stages.

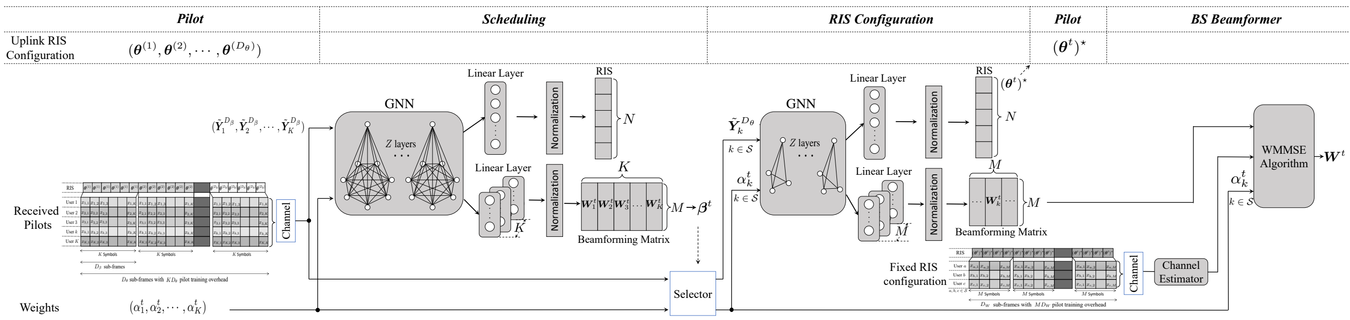


Fig. 4: Three-stage framework for scheduling, RIS configuration and BS beamforming design.

3. PROPOSED DATA-DRIVEN APPROACH

3.1. Graph Neural Networks

A key building block of the proposed learning approach is a GNN architecture that takes the received pilots and the user weights as inputs and produces the RIS configuration and BS beamformers as output. The use of GNN is crucial, because the proposed GNN architecture allows certain permutation invariant and equivariant properties to be observed. That is, if the ordering of users is permuted, the neural network should permute the set of beamforming vectors accordingly, while keeping the same schedule and the same RIS configuration. The earlier work [10] shows that such a GNN can be trained to generate interpretable RIS configuration and beamformers, but only for the setting in which the user schedule is fixed a priori, i.e., only to solve a continuous optimization problem. In this paper, we tackle a mixed discrete and continuous optimization problem — a more challenging setting in which the schedule also needs to be optimized.

The GNN architecture adopted here is similar to the one in [10] in which the permutation invariance and equivariance properties still hold, but with a key difference that the priority weights for the users are used as input to the GNN. Adding priority weights in the neural network for scheduling is in general highly nontrivial, because the system parameters can be very sensitive to small perturbations in the weights [12], which makes the functional landscape difficult to sample. Thus, a generic neural network is unable to learn to schedule and to beamform simultaneously. For this reason, this paper adopts a three-stage framework to first derive the schedule using one GNN, then the RIS profile using another GNN, and lastly the beamformers.

3.2. Three-Stage Framework

Training a single GNN to directly obtain the solution to the problem (7) is challenging, because such a GNN would have $K+1$ nodes, where K can be large, and each node would be associated with high-dimensional input features over D sub-frames of pilot length. To address this scalability issue, we propose the following three-stage framework. A GNN with $(K+1)$ nodes over D_β pilot sub-frames is adopted in the first stage to produce the scheduling of up to M users, where D_β can be as small as 1. Then, another GNN with $(M+1)$ nodes over D_θ pilot sub-frames is adopted in the second stage to produce the optimized RIS configuration, where D_θ is considerably larger than D_β. Finally, a third stage refines the BS beamformers.

3.2.1. Scheduling

In the first stage, a GNN with $K+1$ nodes is used to learn the optimized schedule from a set of very short pilots of D_β sub-frames. The idea is that unlike BS beamforming or RIS configuration, which are strong functions of the channel, scheduling can be done with only a coarse estimation of the overall channel strength or directions. In practice, the D_β sub-frames can be part of the overall D_θ sub-frames of received pilots, since the channels are constant within the coherence time. In the training phase, we use a differentiable loss function, the weighted sum-rate of K users, i.e., $-\mathbb{E}\left[\sum_{k=1}^{K}\alpha_k^t R_k^t\right]$.

Since at this stage, we only used very short received pilots to train the GNN, reflection coefficients and the beamforming vectors learned by the GNN are quite suboptimal, but it is good enough to produce a good scheduling decision. Given the beamforming vectors $\boldsymbol{w}_k^t$'s learned by the GNN, a user with larger beamforming power is more likely to be scheduled than those with smaller beamforming power. Thus, we select M users with the highest powers from the set $\{\|\boldsymbol{w}_1^t\|^2, \cdots, \|\boldsymbol{w}_K^t\|^2\}$ to form a scheduled user set $\mathcal{S}$.

3.2.2. RIS Configuration

In the second stage, we design better reflection coefficients using a second GNN over the M scheduled users but with longer D_θ pilot sub-frames. Such a GNN has a smaller number of nodes, i.e., $M+1$, so it can take much longer received pilot sequences as input without experiencing training difficulty. In particular, the inputs to the GNN for RIS design are the user weights and D_θ decorrelated received pilot sub-frames of the scheduled users, i.e., $\tilde{\boldsymbol{Y}}_k^{D_\theta}$ with $k \in \mathcal{S}$, as shown in Fig. 4. The GNN is trained to maximize the weighted sum-rate of the M scheduled users, i.e., $-\mathbb{E}\left[\sum_{k\in\mathcal{S}}\alpha_k^t R_k^t\right]$, to produce the optimized RIS configuration $(\boldsymbol{\theta}^t)^\star$.

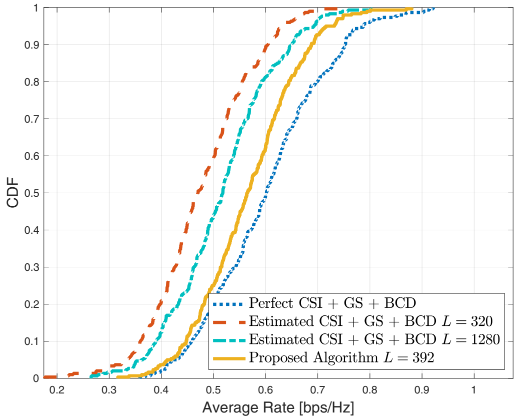
3.2.3. BS Beamforming

Although the BS beamforming vectors are already produced in the previous stages, there is still large room to fine-tune the beamforming vectors with small additional pilot training overhead. With the RIS configuration fixed, the effective combined channel between the BS and the scheduled users is of much lower dimension. Once the channel is estimated, the beamforming matrix $\boldsymbol{W}^t$ can be subsequently designed using the WMMSE algorithm [13].

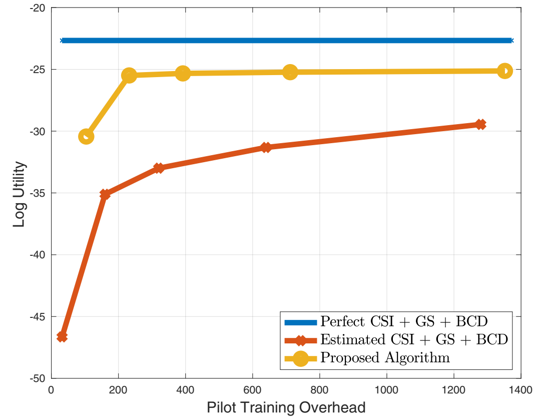
Note that estimating the combined channel vectors perfectly requires only M pilots in the noiseless scenario. At practical SNR, we can use $M \times D_W$ pilot sequences. Let Υ denote the total number of scheduling timeslots in the coherence period. The overall pilot overhead L over all three stages is given by

$$L = K \times D_\theta + M \times D_W \times \Upsilon, \tag{8}$$

where $K \times D_\theta$ accounts for the pilots used to design the schedule and the RIS configuration in the first two stages.



(a) Cumulative distribution function (CDF) of user rates.



(b) Network wide log-utility.

Fig. 5: Performance of GNN based scheduling in an RIS-assisted downlink system with $N = 128$, $M = 8$, $K = 32$, $P_d = 15$ dBm.

4. NUMERICAL RESULTS

4.1. System Setup and Benchmark

We consider an RIS-assisted multiuser MISO network with $M = 8$ BS antennas, $N = 128$ RIS reflective elements, and $K = 32$ users. In the (x, y, z) coordinates, the BS and the RIS are located at $(100m, -100m, 0m)$ and $(0m, 0m, 0m)$ respectively. The user locations are uniformly generated within a rectangular area on the x-y plane $(25 \pm 20m, 17.5 \pm 52.5m, -20m)$. We assume that the direct link channel follows Rayleigh fading, i.e, $\boldsymbol{h}_{\mathrm{d},k} \sim \mathcal{CN}(0, \boldsymbol{I})$ and the reflection channels $\boldsymbol{h}_{\mathrm{r},k}, \boldsymbol{G}$ follow Rician fading model:

$$\boldsymbol{h}_{\mathrm{r},k} = \rho_{1,k}(\sqrt{\epsilon/(1+\epsilon)}\tilde{\boldsymbol{h}}_{\mathrm{r},k}^{\mathrm{LOS}} + \sqrt{1/(1+\epsilon)}\tilde{\boldsymbol{h}}_{\mathrm{r},k}^{\mathrm{NLOS}}), \tag{9a}$$

$$\boldsymbol{G} = \rho_2(\sqrt{\epsilon/(1+\epsilon)}\tilde{\boldsymbol{G}}^{\mathrm{LOS}} + \sqrt{1/(1+\epsilon)}\tilde{\boldsymbol{G}}^{\mathrm{NLOS}}), \tag{9b}$$

where $\rho_{1,k}$ and ρ_2 denote the path losses between the RIS and the k-th user/BS. The path-loss models of the direct and reflected paths are $32.6 + 36.7\log(d_1)$ and $30 + 22\log(d_2)$, respectively, where d_1 and d_2 denote the corresponding link distance. Here, $\tilde{\boldsymbol{h}}_{\mathrm{r},k}^{\mathrm{NLOS}}$ and $\tilde{\boldsymbol{G}}^{\mathrm{NLOS}}$ denote the non-line-of-sight components and their entries are generated independently from the distribution $\mathcal{CN}(0, 1)$. We assume a fast fading channel with $\Upsilon = 5$ scheduling timeslots. The transmission power for uplink and downlink are 15dBm. The bandwidth is 10MHz with a background noise of -170dBm/Hz. The Rician factor ϵ and forgetting factor γ is set to 10 and 0.01. We set $D_\beta = D_W = 1$. We implement two-layer GNN models using Tensorflow [14]; the GNN is trained by Adam optimizer [15].

We compare the proposed data-driven method with the conventional channel estimation based approach. Given the estimated channels [11], a greedy scheduling (GS) method is employed, and the beamforming matrix and the reflection coefficients are optimized by block coordinate descent (BCD) for weighted sum-rate maximization [16]. This baseline is summarized as Algorithm 1.

Algorithm 1 Baseline Greedy Scheduling with BCD

1: Initialize the set of scheduled users $\mathcal{S} = \{\emptyset\}$;
2: Initialize random RIS phase shift vector $\boldsymbol{\theta}^t$;
3: Set $\boldsymbol{w}_k^t = (\boldsymbol{h}_{\mathrm{d},k} + \boldsymbol{A}_k\boldsymbol{\theta}^t), k = 1, \cdots, K$;
4: Compute and sort weighted single-user rate $\alpha_k^t \hat{R}_k^t$ for users:

$$\hat{R}_k^t = \log\left(1 + |(\boldsymbol{h}_{\mathrm{d},k} + \boldsymbol{A}_k\boldsymbol{\theta}^t)^{\mathsf{H}}\boldsymbol{w}_k^t|^2/\sigma_0^2\right), k = 1, \cdots, K; \tag{10}$$

5: Select the user with the largest $\alpha_k^t \hat{R}_k^t$ to add to $\mathcal{S}$;
6: For each unscheduled user, test whether adding that user to $\mathcal{S}$ improves the objective (7). Select the user with the largest improvement to add to $\mathcal{S}$. Repeat until adding another user no longer improves the objective.
7: Fix $\mathcal{S}$ and $\boldsymbol{W}^t$, update $\boldsymbol{\theta}^t$ using the Riemannian conjugate gradient (RCG) algorithm [17];
8: Fix $\mathcal{S}$ and $\boldsymbol{\theta}^t$, update $\boldsymbol{W}^t$ using WMMSE [13];
9: Fix $\boldsymbol{\theta}^t$ and $\boldsymbol{W}^t$, update $\mathcal{S}$ by adding the unscheduled user which improves the objective (7) the most, if any;
10: Repeat step 7-9 until convergence.

4.2. Simulation Results

We examine the performance in terms of proportional fairness criterion in Fig. 5. From Fig. 5(a), the proposed algorithm with 392 pilot symbols is seen to have comparable performance as the benchmark with perfect CSI, and it significantly outperforms the channel estimation based benchmark with 1280 pilots. This implies that the proposed algorithm can achieve much better performance than the conventional method at significantly reduced pilot overhead. From Fig. 5(b), we observe that the proposed algorithm always outperforms the benchmark with imperfect CSI in log utility, especially in the short pilot regime. The performance gain is a consequence of the more efficient processing of the received pilots in designing the schedule and RIS configuration in a data-driven fashion, without explicitly estimating the channels as an intermediary step.

5. CONCLUSIONS

This paper considers a proportional fairness scheduling problem in a multiuser RIS-assisted MISO network. By employing GNNs, the proposed multi-stage framework can jointly optimize the scheduling, beamforming and reflection from the received pilots without explicit channel estimation. Numerical results indicate significant gain over conventional channel estimation based scheduling strategy.

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