Intelligent AP Clustering and Receiver Design for Uplink Cell-free Networks

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Abstract: Cell-free networks can effectively reduce interference due to diversity gain. Two key technologies, access point (AP) clustering and transceiver design, play key roles in cell-free networks, and they are implemented at different layers of the air interface. To address the issues and obtain global optimal results, this paper proposes an uplink joint AP clustering and receiver optimization algorithm, where a cross-layer optimization model is built based on graph neural networks (GNNs) with low computational complexity. Experimental results show that the proposed algorithm can activate fewer APs for each user with a small performance loss compared with conventional algorithms.

Keywords: AP clustering; cell-free networks; cross-layer optimization; graph neural network

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1 Introduction

The 6G mobile communication system[1 – 4] will introduce new application scenarios including immersive cloud extended reality (XR), holographic communication, sensory interconnection, etc. As a result, extremely high transmission metrics have been proposed, including Terabit per second level throughput, microsecond level time delay, 10^7 per square kilometer connection density, and 99.999 9% block error rates (BLERs). The increased number of devices in the network presents a series of challenges for a smaller coverage area of a single base station operated at higher frequency bands. Interference at cell boundaries and frequent switching can result in poor service quality and high deployment costs. Fortunately, cell-free architecture can serve as a potential solution to these problems.

Fig. 1 shows a typical cell-free architecture[5], which consists of a central processing unit (CPU) and a large number of distributed access points (APs) that serve a small amount of user equipment (UE). Each AP is connected to the CPU through a fronthaul link and sends the data received from the users in the uplink to the CPU. The CPU transmits the downlink data and power control parameters to the APs. Due to the short distance between AP and UE, the system can achieve high spatial macro-diversity gain and reduce the path loss.

In the early studies[6 – 7] on cell-free networks, the concept of

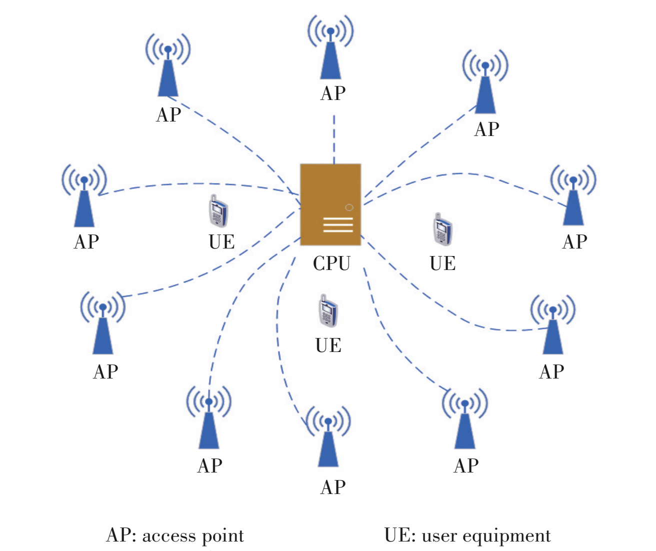

Figure 1. Architecture of cell-free multiple-input multiple-output

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max-min fairness was emphasized, and it was assumed that all APs would provide almost uniform high-quality services to all UE, which would inevitably increase the CPU signal processing complexity and fronthaul overhead. To address this issue, the authors of Ref. [8] proposed a user-centric virtual cell approach to cell-free massive multiple-input multiple-output (MIMO), where each user is served by a limited number of APs, but using a complex approach. In a user-centric cell-free system, how to assign APs to each user, that is AP clustering, and simultaneously perform the beamforming task is the key to improving network performance. A new distributed and scalable algorithm[9] for a user-centric approach in cell-free large-scale MIMO systems is proposed, which jointly addresses initial access, pilot assignment, cooperation cluster formation, precoding, and combining issues. Better results were obtained compared with regularized zero-forcing (RZF), but the issues were individually considered. The authors of Ref. [10] proposed an AP selection algorithm that combines initial access and pilot selection with a complex algorithm. In Ref. [11], a new framework was proposed for the structured massive access in cell-free massive MIMO systems, which comprises one initial access algorithm, a partial large-scale fading decoding (P-LSFD) strategy, two pilot assignment schemes, and one fractional power control policy. New closed-form spectral efficiency (SE) expressions with maximum ratio (MR) were also obtained. The authors of Ref. [12] proposed a joint power allocation and AP selection algorithm, which selected AP through continuous convex optimization. The simulation results showed that the algorithm had significant energy savings, but at the cost of high computational complexity.

Recently, graph neural networks (GNNs) have also been applied in wireless networks[13]. The authors of Ref. [14] proposed an AP selection algorithm based on GNN, which can predict the connection between UE and APs. However, when the number of APs is large, the prediction accuracy decreases. Ref. [15] considered the joint user scheduling and beamforming optimization algorithm based on the GNN algorithm, but it was limited to the downlink system.

Under the premise of considering the maximum linked APs for a single user device, this paper studies and solves the problem of joint optimization of cell-free uplink AP clustering and combining based on historical data and GNN. The main contributions are summarized as follows:

• Aiming to maximize the system rate while considering the maximum active AP number for a user device, this paper constructs a joint optimization model of cell-free uplink AP clustering and combining;

• An intelligent optimization algorithm based on GNN, including problem transformation, two loops of iterative process, etc., is designed to solve the above joint optimization problems;

• Experiment results show that the proposed algorithm has competitive advantages in performance and computational efficiency compared with the traditional clustering optimization ideas.

2 System Model

We consider an uplink cell-free system with B APs and K users, where each AP is equipped with N_t antennas, while each user has a single antenna. The K users are randomly distributed, and the channel coefficient vector between the b-th AP and the k-th user is denoted as $\boldsymbol{h}_{b,k} \in \mathbb{C}^{N_t*1}, b \in \{1,\cdots,B\}, k \in \{1,\cdots,K\}$. $\boldsymbol{w}_{b,k} \in \mathbb{C}^{N_t*1}$ is the corresponding combining beam vector. The transmitting power of the k-th user is $p_k \in \mathbb{C}^{1*1}$. The stacked combining beam vector and channel coefficient vector of the k-th user could be respectively denoted as $\boldsymbol{w}_k = \left[\boldsymbol{w}^{\mathrm{T}}_{1,k},\cdots,\boldsymbol{w}^{\mathrm{T}}_{B,k}\right]^{\mathrm{T}} \in \mathbb{C}^{BN_t*1}$, $\left\|\boldsymbol{w}_k\right\| = 1$ and $\boldsymbol{h}_k = \left[\boldsymbol{h}^{\mathrm{T}}_{1,k},\cdots,\boldsymbol{h}^{\mathrm{T}}_{B,k}\right]^{\mathrm{T}} \in \mathbb{C}^{BN_t*1}$. Assuming that $x_l \in \mathbb{C}^{1*1}$ is the uplink transmitting signal of the l-th user, the received signal could be denoted as follows.

$$\boldsymbol{y} = \sum_{l=1}^{K} p_l \boldsymbol{h}_l x_l + \boldsymbol{n} \tag{1},$$

where $\boldsymbol{n} \in \mathbb{C}^{BN_t \times 1}$ is the complex additive white Gaussian noise with zero mean value and variance σ^2. For convenience, let $\bar{\boldsymbol{h}}_k = \boldsymbol{h}_k/\sigma$ (channel estimation is another topic in wireless networks[19]).

As shown in Fig. 2, several AP clusters are formed in an uplink cell-free network, in which each user is served by various APs, and one AP may link various users. Here, an auxiliary variable $u_{b,k} \in \{0,1\}$ is introduced to represent the link status between the b-th AP and the k-th user. $u_{b,k} = 1$ means that the b-th AP serves the k-th user, otherwise not. Then, we have

$$\bar{x}_k = \bar{\boldsymbol{w}}_k^H \boldsymbol{y} \tag{2},$$

where

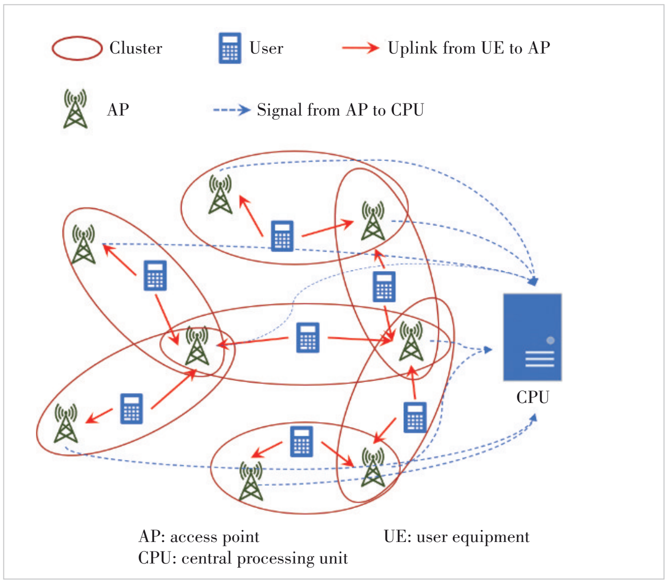

Figure 2. Joint AP clustering and beamforming for uplink cell-free networks

$$\bar{\boldsymbol{w}}_k = \boldsymbol{Q}_k \boldsymbol{w}_k \tag{3},$$

$$\boldsymbol{Q}_k = \begin{bmatrix} u_{1,k}\boldsymbol{I}_{N_t \times N_t} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & u_{B,k}\boldsymbol{I}_{N_t \times N_t} \end{bmatrix} \tag{4}.$$

Thus, the signal-to-noise-ratio (SINR) of the k-th user is formulated as follows:

$$\mathrm{SINR}_k = \frac{\Re_k}{I_k + 1} \tag{5},$$

where $\Re_k = p_k \sum_{b=1}^{B} u_{b,k} \left| \boldsymbol{w}_{b,k}^H \bar{\boldsymbol{h}}_{b,k} \right|^2$ and $I_k = \sum_{b=1}^{B} u_{b,k} \sum_{l=1, l \neq k}^{K} p_l \left| \boldsymbol{w}_{b,k}^H \bar{\boldsymbol{h}}_{b,l} \right|^2$.

In this work, the joint optimization problem of uplink clustering and combining design is considered, which is formulated as:

$$\begin{aligned} &P1: \max_{u_{b,k}, \boldsymbol{w}_k} \sum_{k \in \{1,2,\cdots,K\}} \log\left(1 + \mathrm{SINR}_k\right) \\ &\text{s.t. } C1: \sum_{b = \{1,\cdots,B\}} u_{b,k} \leqslant N, \forall k \in \{1,\cdots,K\} \\ &C2: \left\| \boldsymbol{w}_k \right\|_2 = 1, \forall k \in \{1,\cdots,K\} \\ &C3: u_{b,k} \in \{0,1\}, \forall b \in \{1,\cdots,B\}, k \in \{1,\cdots,K\} \end{aligned} \tag{6}.$$

In the above problem, constraint $C1$ assumes that the maximum number of linked APs for each user is N, where $N \leqslant B$. Constraint $C3$ specifies that there are only two states between the user and each AP, i.e., linked and non-linked. Constraint $C2$ ensures that the beam vectors are normalized. It is noted that $P1$ is a non-convex integer programming problem, which is difficult to solve directly. Inspired by the experimental result that GNN outperforms convolutional neural networks in handling wireless network topology information in Ref. [15], we adopt GNN to accomplish the above task in the following section.

3 Optimization Method

3.1 Problem Transformation

To simplify the integer programming problem, constraint $C3$ is first equivalently transformed into the following form:

$$C4: 0 \leqslant u_{b,k} \leqslant 1, \forall b \in \{1,\cdots,B\}, k \in \{1,\cdots,K\} \tag{7},$$

$$C5: \sum_{b \in \{1,\cdots,B\}, k \in \{1,\cdots,K\}} \left(u_{b,k} - u_{b,k}^2\right) \leqslant 0 \tag{8}.$$

Introducing the nonconvex constraint $C5$ into the objective function of $P1$ using a Lagrange multiplier μ, the original problem $P1$ is transformed into the following max-min problem $P2$.

$$\begin{aligned} &P2: \max_{\mu} \min_{u_{b,k}, \mathbf{w}_k} - \sum_{k \in \{1,2,\cdots,K\}} \log\left(1 + \mathrm{SINR}_k\right) + \\ &\mu \chi_C^{\geqslant} \sum_{b \in \{1,\cdots,B\}, k \in \{1,\cdots,K\}} \left(u_{b,k} - u_{b,k}^2\right) \\ &\text{s.t. } C1, C2, C4 \end{aligned} \tag{9},$$

where $\chi_C^{\geqslant}(a) = \max(a,0)$ is a penalty function to measure the violation degree of constraint $C5$, which adopts an element-wise operation form. In Problem $P2$, constraints $C1$ and $C4$ are convex, and objective function is nonconvex with a complex form. To solve this problem, a two-loop iterative approach is designed. In the outer loop, $u_{b,k}$ and $\boldsymbol{w}_k$ are fixed, and we update μ using the formula:

$$\mu = \mu + \varepsilon_u \chi_C^{\geqslant} \sum_{b \in \{1,\cdots,B\}, k \in \{1,\cdots,K\}} \left(u_{b,k} - u_{b,k}^2\right) \tag{10},$$

where ε_u represents the step size. In the inner loop, μ is fixed, and we aim at obtaining $u_{b,k}$ and $\boldsymbol{w}_k$ by solving the following problem.

$$\begin{aligned} &P3: \Psi \triangleq \min_{u_{b,k}, \boldsymbol{w}_k} \Bigg(- \sum_{k \in \{1,2,\cdots,K\}} \log\left(1 + \mathrm{SINR}_k\right) + \\ &\mu \chi_C^{\geqslant} \sum_{b \in \{1,\cdots,B\}, k \in \{1,\cdots,K\}} \left(u_{b,k} - u_{b,k}^2\right) \Bigg) \\ &\text{s.t. } C1, C2, C4 \end{aligned} \tag{11},$$

To solve Problem $P3$, $\boldsymbol{w}_k$ could be estimated with the minimum mean square error (MMSE) approach as follows.

$$\boldsymbol{w}^*_k = \frac{\left(\boldsymbol{I} + \sum_{l \in K} p_l \tilde{\bar{\boldsymbol{h}}}_l \tilde{\bar{\boldsymbol{h}}}_l^H\right)^{-1} \tilde{\bar{\boldsymbol{h}}}_k}{\left\| \left(\boldsymbol{I} + \sum_{l \in K} p_l \tilde{\bar{\boldsymbol{h}}}_l \tilde{\bar{\boldsymbol{h}}}_l^H\right)^{-1} \tilde{\bar{\boldsymbol{h}}}_k \right\|} \tag{12},$$

where $\tilde{\bar{\boldsymbol{h}}}_k = \boldsymbol{Q}_k \bar{\boldsymbol{h}}_k$. Then, given $\boldsymbol{w}_k$, we solve Problem $P2$ using GNN to obtain $u_{b,k}$.

3.2 Intelligent Optimization Framework

In this section, an intelligent optimization framework using GNN is proposed to solve Problem $P2$. As shown in Fig. 3, the framework consists of inner and outer loops. In the outer loop, $u_{b,k}$ and $\boldsymbol{w}_k$ are fixed, and we update μ using Eq. (10). In the inner loop, $u_{b,k}$ is first fixed and we obtain $\boldsymbol{w}_k$ using Eq. (12). Then, $\boldsymbol{w}_k$ is fixed and a GNN based approach is designed to obtain $u_{b,k}$ in the inner loop. Four parts comprise the inner loop. Specifically, the graph representation layer builds a graph that can be applied for subsequent processing; the graph convolution neural network (GCN) layer extracts features from the constructed graph, and outputs optimal $u_{b,k}$; the projection layer projects the output results into the feasible region to meet constraints $C1$ and

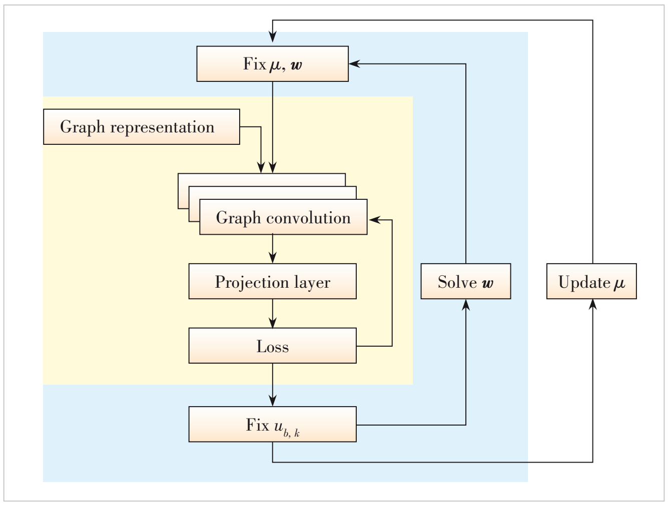

Figure 3. Intelligent iterative optimization framework

$C4$; the loss function layer calculates the loss of the network. These parts are discussed in detail in the following sections.

3.3 Knowledge Graph Representation

The foundation for using GNNs in wireless communication networks is to model the network as a graph, where nodes and edges are assigned feature information. This graph can then be processed by GCN[16–17]. The key step in constructing a knowledge graph representation is to define the triples in wireless networks, which consist of head entities, tail entities, and their relationships.

The knowledge graph can be denoted as $G = (V,E)$, where V is the set of nodes and E is the set of edges. In the paper, the communication links between APs and users are regarded as nodes, while the interference links between users are regarded as edges. The features of nodes and edges are characterized by channel vectors and other state information, as shown in Fig. 4. Specifically, for the i-th node $v_i \in V$, its node feature is defined as $\boldsymbol{x}_i = \left(\left|\bar{\boldsymbol{h}}_{i,1}^H \bar{\boldsymbol{h}}_{i,1}\right|, \cdots, \left|\bar{\boldsymbol{h}}_{i,B}^H \bar{\boldsymbol{h}}_{i,B}\right|\right) \in \mathbb{C}^{B*1}$, and the edge feature of $\boldsymbol{e}_{ij} = \left(v_i, v_j\right) \in E$ is defined as $\boldsymbol{e}_{i,j} = \left|\bar{\boldsymbol{h}}_i^H \bar{\boldsymbol{h}}_j\right| \in \mathbb{C}^{1*1}, j \in \mathcal{N}_i$, where $\left(v_i, v_j\right) \in E$ means the edges of nodes v_i and v_j, and $\mathcal{N}_i$ is the set of adjacent nodes of v_i. From the definition, we can see that a node represents the communication link between a user and an AP, while an edge represents the interference link between users. In the inner iteration process, we initialize the constructed graph G and the objective solution $u_{b,k}$, and then use them as the input to GNN.

3.4 Structure of GCN

Fig. 5 shows the structure of GCN, which comprises message generation, message aggregation, and node updating. Inspired by Ref. [18], we update the rule of the i-th node in layer l as follows.

$$\begin{aligned} \boldsymbol{g}_i^{(l)} &= \boldsymbol{G}\left(\left\{\boldsymbol{M}_\theta^{(l)}\left(\boldsymbol{\beta}_j^{(l-1)}, \boldsymbol{x}_j, \boldsymbol{e}_{j,i}\right), j \in \mathcal{N}_i\right\}\right) \\ \boldsymbol{\beta}_i^{(l)} &= \boldsymbol{T}_\theta^{(l)}\left(\boldsymbol{\beta}_i^{(l-1)}, \boldsymbol{x}_i, F_{\text{norm}}\left(\boldsymbol{x}_i, \boldsymbol{g}_i^{(l)}\right)\right), i \in \mathcal{V} \end{aligned} \tag{13}$$

In Eq. (13), $\boldsymbol{M}_\theta^{(l)}(\cdot)$ is a message generation function, $T_\theta^{(l)}$ is an updating function, and they are realized using different deep neural networks. $\boldsymbol{G}(\cdot)$ is a message aggregation function and it is applied to aggregate information of nodes. $\boldsymbol{\beta}_i^{(l)} \triangleq \left[u_{:,i}, p_i\right] \in \mathbb{R}^{B+1}$ represents the input vector of the i-th node in the l-th layer GCN. $F_{\text{norm}}(\cdot)$ is applied to normalized $\boldsymbol{g}_i^{(l)}$ with the following form:

$$F_{\text{norm}}\left(\boldsymbol{x}_i, \boldsymbol{g}_i^{(l)}\right) = \left\|\boldsymbol{x}_i\right\|_2 \frac{\boldsymbol{g}_i^{(l)}}{\left\|\boldsymbol{g}_i^{(l)}\right\|_2}, i \in \mathcal{V}. \tag{14}$$

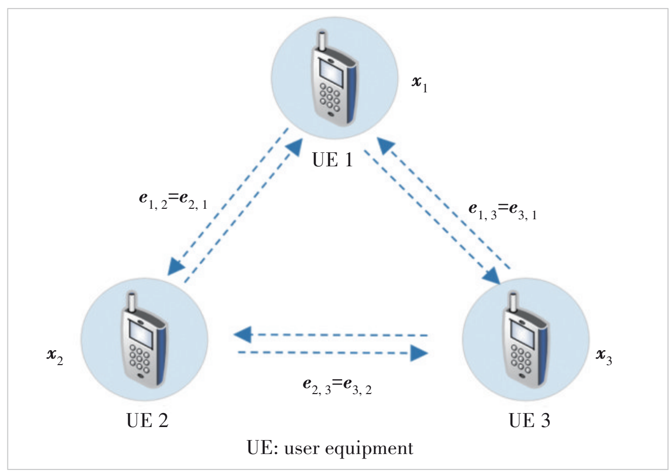

Figure 4. Knowledge graph representation of uplink transmission

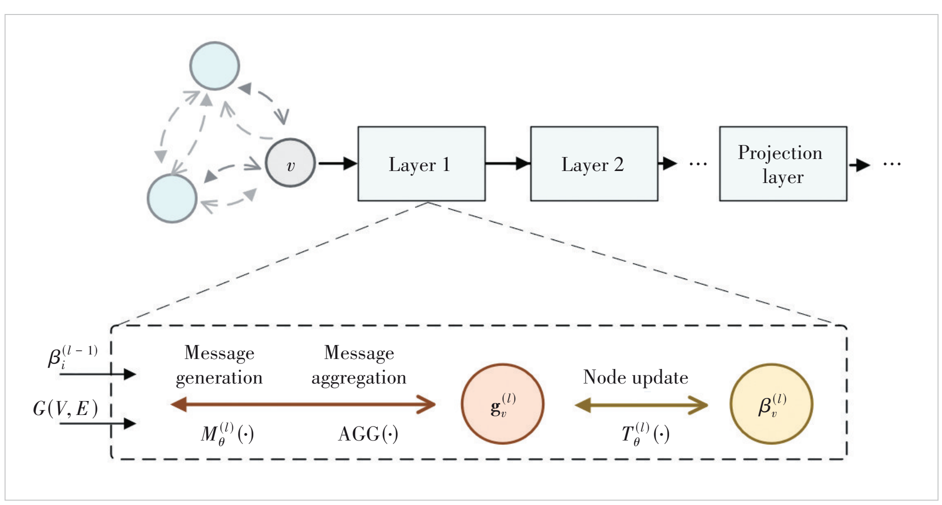

Figure 5. Structure of the proposed graph neural network

3.5 Projection Layer

GNN could obtain $u_{b,k}$ from optimizing $P3$ in the above subsections, without considering the convex constraint $C1$ or $C4$. In this section, an individual projection layer is considered for post-processing $u_{b,k}$ to satisfy constraints $C1$ and $C4$. A projection operator is designed as shown in Eq. (15). It can be easily found that $u_{b,k}$ takes values in the interval [0, 1] (Constraint $C4$), and its summation value is less than N (Constraint $C1$).

$$\Omega_1 \triangleq \left\{ u_{b,k}{}^{(*)} = \frac{N}{\max\left\{ \sum_{b=\{1,\cdots,B\}} u_{b,k}{}',N \right\}} u_{b,k}{}' \right\} \quad (15),$$

where $u_{b,k}{}' = \min\left(\max\{u_{b,k},0\},1\right)$.

4 Experiment

4.1 Parameter Settings

This section reports simulated experimental results using the proposed algorithm. In the experiment, users are randomly distributed and they share the same noise variance, namely, $\sigma_k^2 = \sigma^2, \forall k \in \{1,\cdots,K\}$. The radius of the cell is 300 m, and the minimum distance between the user and AP is 200 m. The signal-to-noise ratio (SNR) of the AP is designed as SNR = $10\log(\frac{P}{\sigma^2})$ dB. Updating the step size of ε_u is 1×10^{-5}. The maximum iteration epoch is 200, and the iteration stopping threshold is 1×10^{-3}. An Adam optimizer is adopted, and the learning rate is 1×10^{-4}. The Monte Carlo method is used and the average sum rate is the final value. Besides the proposed algorithm, two approaches are also applied as the baselines. In Baseline 1, for each user, N APs with the optimal channels will be chosen as a cluster. In Baseline 2, all APs will be applied to serve all users.

4.2 Experiment Results

1) Experiment 1: small-scale experiment results

In the small-scale experiment, experiment simulation parameters are shown in Table 1.

Table 1. Default experiment simulation parameters

Default System Parameter	Value
AP number, B	7
Antenna number of AP, N_t	4
User number, K	3
Antenna number of user	1
SNR/dB	0, 10, 20
Transmitting power of UE, p_k	1 W
Training number	20 000
Testing number	2 000
Maximum link AP number of UE, N	4
Noise variance, σ	1

AP: access point SNR: signal-to-noise ratio UE: use equipment

Table 2. Average sum rate in Experiment 1

	SNR/dB	Proposed/ ($\text{bit}\cdot\text{s}^{-1}\cdot\text{Hz}^{-1}$)	Baseline 1/ ($\text{bit}\cdot\text{s}^{-1}\cdot\text{Hz}^{-1}$)	Baseline 2/ ($\text{bit}\cdot\text{s}^{-1}\cdot\text{Hz}^{-1}$)
$N = 4$	0	4.279 9	4.585 3	4.613 7
	10	20.344 5	21.088 6	21.398 4
	20	40.108 5	41.182 2	41.256 3

SNR: signal-to-noise ratio

Table 3. Average linked access point number in Experiment 1

	SNR/dB	Proposed	Baseline 1	Baseline 2
$N = 4$	0	3.039	4	7
	10	3.055	4	7
	20	3.045	4	7

SNR: signal-to-noise ratio

In Tables 2 and 3, Baseline 2 applies all seven APs to serve users, thus obtaining the optimal results. In contrast, Baseline 1 selects the four APs with the best channel condition for one user, resulting in a performance loss of less than 2% while reducing linked APs. Moreover, fewer APs are linked using the proposed algorithm, with a performance loss of less than 7% compared with Baseline 1.

2) Experiment 2: large-scale experiment results

In the large-scale experiment, AP number B is 21, user number K is 10, and the maximum linked AP number N is 2. Other simulation parameters are the same as in Table 1.

In the large-scale experiment, all 21 APs are applied to serve 10 users for Baseline 2, which brings the best sum rate performance. Baseline 1 chooses 2 APs for each user device, and it obtains about 5% performance loss when SNR is 20 dB, but the performance loss increases if SNR is 0 dB. The proposed method tends to apply fewer APs to serve UE, but at the cost of about 5% performance loss compared with Baseline 1.

4.3 Computational Complexity

In Tables 4 and 5, the average sum rate and average linked access point are respectively listed. The computational complexity of the proposed algorithm, and Baselines 1 and 2 are shown in Table 6. The results show that the proposed method has competitive computational complexity compared with Baselines 1 and 2. In small-scale networks, the computational complexity of the proposed method is about 80% and 72% of Baselines 1 and 2, respectively. The advantage increases in large-scale networks, and the ratios are about 52% and 42%.

5 Conclusions

This paper proposes an intelligent optimization algorithm based on GNNs to solve the joint optimization problem of AP clustering and beamforming in uplink massive cell-free networks. We first construct an optimization model with the goal of maximizing the system's sum rate, and solve it under the con-

Table 4. Average sum rate in Experiment 2

	SNR/dB	Proposed/ (bit·s^{-1}·Hz^{-1})	Baseline 1/ (bit·s^{-1}·Hz^{-1})	Baseline 2/ (bit·s^{-1}·Hz^{-1})
N = 2	0	5.065 7	5.535 6	7.116 7
	10	40.438 0	42.832 3	47.354 0
	20	99.548 2	105.068 7	110.738 1

SNR: signal-to-noise ratio

Table 5. Average linked access point number in Experiment 2

	SNR/dB	Proposed	Baseline 1	Baseline 2
N = 2	0	1.428	2	21
	10	1.241	2	21
	20	1.225	2	21

SNR: signal-to-noise ratio

Table 6. Comparison of computational complexity

Algorithms	Experiments	Proposed	Baseline 1	Baseline 2
Computational complexity	Experiment 1	76 512	95 296	106 624
	Experiment 2	1 249 600	2 404 736	2 935 296

straint of considering the maximum number of APs linked with a single user. This paper transforms the wireless network resource optimization problem into a graph optimization problem and leverages GNN to solve it. Simulation experiments show that the proposed algorithm allocates fewer APs to serve a single user than traditional methods at the cost of a small performance loss.

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