Joint User Scheduling and Beamforming Design for Multiuser MISO Downlink Systems

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Abstract—In multiuser communication systems, user scheduling and beamforming (US-BF) design are two fundamental problems that are usually studied separately in the existing literature. In this work, we focus on the joint US-BF design with the goal of maximizing the set cardinality of scheduled users, which is computationally challenging due to the non-convex objective function and the coupled constraints with discrete-continuous variables. To tackle these difficulties, a successive convex approximation based US-BF (SCA-USBF) optimization algorithm is firstly proposed. Then, inspired by wireless intelligent communication, a graph neural network based joint US-BF (J-USBF) learning algorithm is developed by combining the joint US and power allocation network model with the BF analytical solution. The effectiveness of SCA-USBF and J-USBF is verified by various numerical results, the latter achieves close-to-analytical solution. The effectiveness of SCA-USBF and J-USBF joint US and power allocation network model with the BF (J-USBF) learning algorithm is developed by combining the joint US and power allocation network model with the BF analytical solution. The effectiveness of SCA-USBF and J-USBF is verified by various numerical results, the latter achieves close performance and higher computational efficiency. Furthermore, the proposed J-USBF also enjoys the generalizability in dynamic wireless network scenarios.

Index Terms—Cross-layer optimization, user scheduling, beamforming design, graph neural networks, non-convex optimization.

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I. INTRODUCTION

With the explosive growth of Internet of Things (IoT) devices, wireless communication networks (WCNs) are increasingly facing the challenge of allocating finite transmit power and bandwidth for system utility maximization [1]. Accordingly, one needs to design advanced radio resource management schemes to serve numerous wireless access devices. Massive multiple-input multiple-output (MIMO) and multiuser transmission are two key enablers for supporting larger-scale connection in future WCNs [2]. Therefore, some works have been carried on researching the beamforming design (BF) [3], power allocation (PA) [4], and user scheduling (US) [5], etc.

Generally speaking, US and BF (US-BF) design are two fundamental problems in multiuser WCNs, which are implemented at the media access control layer [6] and the physical layer [7], respectively. Unfortunately, these two issues are always coupled, which is difficult to be solved. Therefore, they are generally investigated separately in the existing literature, such as BF design with a given user set [8] or US optimization combined with PA (US-PA) [9]. For example, the authors of [10] and [11] only consider the BF problem, where the uplink-downlink duality theory is adopted for tackling the non-convex problem of transceivers design. The authors of [12] and [13] also solve the BF problem for RIS-empowered Terahertz communications with deep reinforcement learning methods. To further improve the performance of WCNs, cross-layer design is increasingly becoming popular [14]. The authors of [15] investigate the US-BF problem by sequentially performing the semi-orthogonal user selection (SUS) algorithm for US optimization and the zero-forcing BF (ZFBF) algorithm for BF design. The authors of [16] propose a low complexity US-BF scheme for 5G MIMO nonorthogonal multiple-access systems, but the non-convex problem is separated by tracking two subproblems, namely, BF scheme and greedy min-power US scheme, instead of jointly solving them. The authors of [17] also discuss cross layer optimization with statistical channel information for massive MIMO scenario, by tackling US and BF individually.

Meanwhile, the existing researches on coordinated multiuser communication are mainly based on the conventional Shannon theory [18], which assumes that the communication capacity has extremely low decoding error probability with enough long blocklength transmission. However, in the ultra-reliable low
latency communication (URLLC) scenarios, such as factory automation and remote surgery, this condition with the long blocklength transmission may not be satisfied [19]. To take the impact of finite blocklength transmission into account, the achievable rate has been expressed as a complicated function composed of the received signal-to-noise (SNR), the blocklength, and the decoding error probability, which is smaller than the Shannon rate [20]. Consequently, the optimization problem in scenarios with finite blocklength transmission is more challenging [21]. In order to solve the problem of interest, the algorithms designed in the aforementioned references are mainly based on the convex optimization theory [22]. However, such model-driven optimization algorithms usually suffer from a high computational complexity, which may restrict their practical application ability in WCNs.

Recently, deep neural networks (DNNs) have emerged as an effective tool to solve such challenging radio resource management problems in WCNs [23]. Different from the model-driven optimization algorithms running independently for each instance, DNNs are trained with numerous data to learn the mapping between radio resource optimization policies and WCN environments. Hence, the main computational cost of DNNs is shifted into the offline training stage, and only simple mathematical operations are needed in the online optimization stage. The work in [24] shows that DNNs could achieve competitive performance with lower computational complexity than existing model-driven optimization algorithms. A similar conclusion has been demonstrated in [25], where DNNs are used for BF design of multiuser multiple-input single-output (MISO) downlink systems, but the size of the considered problem is rather small. The authors of [26] regard resource allocation problems in the field of wireless communications as the generalized assignment problems (GAP), and propose a novel deep unsupervised learning approach to solve GAP in a time-efficient manner. The authors of [27] focus on solving PA problem via ensembling several deep neural networks. This is also an unsupervised approach and achieves competitive results compared with conventional methods. However, the core network is specifically designed for power control problem and it could not be extended for US. In addition, these DNN-based architectures [24], [25], [26], [27] are mainly inherited from image processing tasks and not tailored to radio resource management problems, especially the fact that they fail to exploit the prior topology knowledge in WCNs. The numerical results obtained in [28] illustrated that the performance of DNNs degrades dramatically with increasing WCN size.

To achieve a better scalability of learning-based radio resource management, a potential approach is to incorporate the network topology into the learning of neural networks, namely graph neural networks (GNNs) [29]. For instance, the authors of [30] combined DNNs with the geographic location of transceivers, and thereby proposed a spatial convolution model for wireless link scheduling problems with hundreds of nodes. The authors of [31] proposed a random edge graph neural network (REGNN) for PA optimization on graphs formed by the interference links within WCNs. The work in [32] demonstrates that GNNs are insensitive to the permutation of data, such as channel state information (CSI). Further, this work was extended in [33] to solve both PA and BF problems via message passing graph neural networks (MPGNNs), which have the ability to generalize to large-scale problems while enjoying a high computational efficiency. However, their proposed designs in [32] and [33] only investigated the continuous optimization problems with simple constraints. The discrete optimization problems with complicated constraints are still an opening issue and need to be further considered. Fortunately, the application of primal-dual learning in [34] provides an effective way to solve the complicated constrained radio resource management problems.

Based on the above considerations, this work studies the joint US-BF optimization problem in the multiuser MISO downlink system. Unlike the conventional methods, the US-BF design will be simultaneously achieved via solving a single optimization problem, instead of different problems. Moreover, to improve the computational efficiency and utilize network historical data information, we propose a GNN-based Joint US-BF (J-USBF) learning algorithm. The main contributions and advantages of this work are summarized as follows:

- A joint US-BF optimization problem for multiuser MISO downlink systems is formulated with the goal of maximizing the number of scheduled users subject to user rate and base station (BS) power constraints. To solve this discrete-continuous variables optimization problem, a SCA-based US-BF (SCA-USBF) algorithm is firstly designed to pave the way for the J-USBF algorithm.
- A J-USBF learning algorithm is developed by combining the joint user scheduling and power allocation network (JEEPON)\(^{1}\) model with the BF analytical solution. In particular, we first formulate the investigated problem as a graph optimization problem through wireless graph representation, then design a GNN-based JEEPON model to learn the US-PA strategy on graphs, and utilize the BF analytical solution to achieve joint US-BF design. Meanwhile, a primal-dual learning framework is developed to train JEEPON in an unsupervised manner.
- Finally, numerical results is conducted to validate the effectiveness of the proposed algorithms. Compared with the SCA-USBF algorithm, the J-USBF learning algorithm achieves close performance and higher computational efficiency (computational complexity decrease at least 90% when the number of users is 200), and enjoys the generalizability in dynamic WCN scenarios.

1The letters of abbreviation JEEPON are all extracted from the expression “Joint usEr schEduling and Power allOcation Network”, for the convenience of reading.
Notations: Throughout this paper, lowercase and uppercase letters (such as \(a\) and \(A\)) represent scalars, while the bold counterparts \(\mathbf{a}\) and \(\mathbf{A}\) represent vectors and matrices, respectively. \(|\cdot|\) indicates the absolute value of a complex scalar or the cardinality of a set. \(\|\cdot\|_0, \|\cdot\|_1,\) and \(\|\cdot\|_2\) denote the \(\ell_0\)-norm, \(\ell_1\)-norm, and \(\ell_2\)-norm, respectively. The superscripts \((\cdot)^T\), \((\cdot)^H\), and \((\cdot)^{-1}\) denote the transpose, conjugate transpose, and inverse of a matrix, respectively. \(\mathbb{R}, \mathbb{R}^+,\) and \(\mathbb{C}\) are the sets of real, non-negative real, and complex numbers, respectively. Finally, \(\mathbb{R}^{M \times 1}\) and \(\mathbb{C}^{M \times 1}\) represent \(M\)-dimensional real and complex column vectors, respectively.

II. System Model and Problem Formulation

In this work, we consider a multiser user MISO downlink system with taking the reliable and delivery latency into account, where a BS with \(N\) antennas serves \(K\) single-antenna users. For simplicity, let \(\mathcal{K} = \{1, 2, \cdots, K\}\) and \(\mathcal{S} = \{1, 2, \cdots, K^*\} \subseteq \mathcal{K}\) be the set of candidate users and scheduled users, respectively, where \(K^* \leq K\). The channel between user \(k\) and the BS is denoted as \(h_k \in \mathbb{C}^{N \times 1}\). Let \(p_k \geq 0\) and \(w_k \in \mathbb{C}^{N \times 1}\) represent the transmit power and unit-norm BF vector used by the BS for user \(k\), respectively. Thus, the received signal at user \(k\) is given by

\[
y_k = \sum_{l \in \mathcal{S}} \sqrt{p_l} h_k^H w_l s_l + n_k, \tag{1}
\]

where \(s_l\) is the normalized data symbol intended for the \(l\)-th user, and \(n_k \sim \mathcal{CN}(0, \sigma_k^2)\) denotes the additive Gaussian white noise at user \(k\) with zero mean and variance \(\sigma_k^2\). For notational convenience, we define \(\bar{h}_k = \frac{h_k}{\|h_k\|_2}\) and the downlink signal-to-interference-plus-noise ratio (SINR) of user \(k\) as

\[
\gamma_k = \frac{p_k \|h_k^H w_k\|^2}{\sum_{l=1, l \neq k}^{K} p_l \|h_k^H w_l\|^2 + 1}.
\]

To satisfy the extreme requirements of delay, finite blocklength transmission is adopted in this paper. The results in [20] show that the achievable rate is not only a function of the received SNR (or SINR), but also the decoding error probability \(\epsilon\) and the transmission finite blocklength \(n\). Accordingly, the achievable rate of user \(k\) with finite blocklength transmission is given by

\[
R(\gamma_k) = C(\gamma_k) - \vartheta \sqrt{V(\gamma_k)},
\]

where \(C(\gamma) = \ln(1 + \gamma)\) denotes the Shannon capacity, \(\vartheta = \frac{Q^{-1}(\epsilon)}{\sqrt{n}}\) is the inverse of Gaussian Q-function, \(Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^\infty \exp(-\frac{t^2}{2}) dt\), and \(V(\gamma_k)\) denotes the channel dispersion, which is defined as

\[
V(\gamma_k) = 1 - \frac{1}{(1 + \gamma_k^2)^2}.
\]

The target of this work is to maximize the number of users belonging to the scheduled user set \(\mathcal{S} \subseteq \mathcal{K}\) subject to the constraints of per-user minimum rate requirement and BS maximum power budget. Specifically, one needs to carefully select the scheduled user set \(\mathcal{S}\), and design BF vectors with reasonable transmit power. To this end, the joint US-BF optimization problem is formulated as follows

\[
\begin{align*}
\max_{\{p_k, w_k\}} & \quad |\mathcal{S}|, \\
\text{s.t.} & \quad r_k \leq R(\gamma_k), \quad \|w_k\|_2 = 1, \forall k \in \mathcal{S}, \tag{5a} \\
& \quad \sum_{k \in \mathcal{S}} p_k \leq P, \quad p_k \geq 0, \forall k \in \mathcal{S}, \tag{5b}
\end{align*}
\]

where \(|\mathcal{S}|\) is the cardinality of set \(\mathcal{S}\), \(r_k\) is the per-user minimum rate requirement, and \(P\) denotes the power budget of the BS. Problem (5) is a mixed-integer continuous-variable programming problem that involves a discrete objective function and two continuous-variable constraints about power and unit-norm BF vectors. It is difficult to obtain the global optimal solution of problem (5), even the near-optimal solution. Although the greedy heuristic search based US-BF (G-USBF) algorithm in Appendix A could be considered as a possible effective solution, it brings extremely high computational complexity especially for large-scale WCNs. In the sequel, the SCA-based US-BF optimization algorithm and the GNN-based learning algorithm are successively proposed to solve the problem (5).

III. Design of the SCA-USBF Algorithm

In this section, we pay our attention on designing an effective optimization algorithm for problem (5) from the perspective of successive convex approximation (SCA) optimization theory. Since problem (5) is non-convex, the first thing is to transform it into a tractable form via some basic mathematical transformations. One idea is to apply the uplink-downlink duality theory [36] to equivalently transform the downlink problem (5) into a virtual uplink dual problem (6), i.e.,

\[
\begin{align*}
\max_{\{r_k, w_k\}} & \quad |\mathcal{S}|, \\
\text{s.t.} & \quad r_k \leq R(\gamma_k), \quad \|w_k\|_2 = 1, \forall k \in \mathcal{S}, \tag{6a} 
\end{align*}
\]

For the ultra-dense or large-scale connective URLLC scenario, it may be a better choice to schedule as many users as possible while satisfying reliability and latency requirements. Accordingly, we aim to maximize the set cardinality of scheduled users in this work.

In our experiment, we obtain perfect CSI via link level simulation. However, it is indeed hard to estimate CSI in the real communication systems [35]. Although there are pilot-based and blind channel estimation methods, the perfect CSI cannot be obtained due to the estimation error, which may lead to performance deterioration. Statistical CSI, including RSRP (Reference Signal Receiving Power), RSRQ (Reference Signal Receiving Quality), RSSI (Received Signal Strength Indicator), et al., might be helpful under this condition. We would like to further investigate the joint US-BF problem in the future work.

2Since the complexity of discussed problem, the single-cell scenario is considered in this paper. Research on more complex scenario with multi-cells will be discussed in future work, where inter-cell interference should be considered.

3The proposed algorithms is also suitable for solving similar optimization problems, where the user rate is based on Shannon capacity formula.
where \( q_k \) is the virtual uplink transmit power of user \( k \), and \( \gamma_k \) represents the corresponding virtual uplink received SINR, i.e.,

\[
\gamma_k = \frac{q_k |\mathbf{h}_k^H \mathbf{w}_k|^2}{\sum_{l \neq k, l \in \mathcal{K}} q_l |\mathbf{h}_l^H \mathbf{w}_k|^2 + 1}.
\]  

Note that the definition (7) focuses on calculating SINRs for the scheduled user set \( \mathcal{S} \), with its implicit information is that the SINRs of the unscheduled users are all zero values in theory. For convenience, we further propose a new SINR definition \( \tilde{\gamma}_k(\mathcal{K}) \) which is directly calculated based on the candidate user set \( \mathcal{K} \), i.e.,

\[
\tilde{\gamma}_k(\mathcal{K}) = \frac{q_k |\mathbf{h}_k^H \mathbf{w}_k|^2}{\sum_{l \neq k, l \in \mathcal{K}} q_l |\mathbf{h}_l^H \mathbf{w}_k|^2 + 1}.
\]  

To clearly indicate whether a user is scheduled or not, we introduce \( \kappa_k (k \in \mathcal{K}) \) as a binary variable indicator of the user state, with \( \kappa_k = 1 \) if the \( k \)-th user is scheduled and \( \kappa_k = 0 \) if the \( k \)-th user is unscheduled. Recalling that \( \mathcal{S} \) is not a deterministic set, and changes dynamically with different scheduled users, which makes it significantly difficult to solve problem (6). Therefore, to release the uncertainty of \( \mathcal{S} \), let \( \kappa = [\kappa_1, \kappa_2, \ldots, \kappa_k, \ldots, \kappa_K]^T \), then problem (6) can be approximately written as

\[
\max_{\kappa, q, \mathbf{w}_k} \|\kappa\|_0, \quad \text{s.t.} \quad k_k \in \{0, 1\}, \forall k \in \mathcal{K}, \quad \kappa_k r_k \leq R(\gamma_k), \quad \|\mathbf{w}_k\|_2 = 1, \forall k \in \mathcal{K}, \quad \sum_{k \in \mathcal{K}} q_k \leq P, \quad q_k \geq 0, \forall k \in \mathcal{K}. \quad (9c)
\]  

In other words, the solution to problem (6) is the upper bound of problem (9).

The goal of problem (9) is to maximize the number of scheduled users under the given constraints. Further, constraints (9b) and (9c) can be equivalently transformed into continuous constraint type and SINR form [21], respectively. Let \( \tilde{\gamma}_k > 0 \) be the minimum SINR associated with achieving the minimum achievable rate \( r_k \) for the \( k \)-th user. Thus, problem (9) can be equivalently transformed as

\[
\max_{\kappa, q, \mathbf{w}_k} \|\kappa\|_0, \quad \text{s.t.} \quad 0 \leq \kappa_k \leq 1, \forall k \in \mathcal{K}, \quad \sum_{k \in \mathcal{K}} (\kappa_k - \kappa_k^0) \leq 0, \quad \kappa_k \tilde{\gamma}_k \leq \gamma_k, \|\mathbf{w}_k\|_2 = 1, \forall k \in \mathcal{K}, \quad \sum_{k \in \mathcal{K}} q_k \leq P, \quad q_k \geq 0, \forall k \in \mathcal{K}. \quad (10a)
\]  

Constraints (10b) and (10c) assure that the value of \( \kappa_k \) equals to either one or zero, i.e., \( \kappa_k \in \{0, 1\}, \forall k \in \mathcal{K} \). According to [37, Proposition 2], the strong Lagrangian duality holds for problem (10). Introducing similar mathematical tricks on handling constraint (10c), problem (10) is reformulated as follows

\[
\min_{\kappa, q, \mathbf{w}_k} \left( \sum_{k \in \mathcal{K}} \kappa_k + g(\kappa) - h(\kappa) \right), \quad \text{s.t.} \quad (10b), (10d), (10e), \quad (11a)
\]

where \( \lambda \) is a proper non-negative constant, and \( g(\kappa) \) and \( h(\kappa) \) are defined respectively as

\[
g(\kappa) \triangleq \lambda \sum_{k \in \mathcal{K}} \kappa_k^2 + \lambda \left( \sum_{k \in \mathcal{K}} \kappa_k \right)^2, \quad (12a)
\]

and

\[
h(\kappa) \triangleq \lambda \sum_{k \in \mathcal{K}} \kappa_k^2 + \lambda \left( \sum_{k \in \mathcal{K}} \kappa_k \right)^2. \quad (12b)
\]

Note that the optimal receiver BF vector \( \mathbf{w}_k^{(s)} \) for maximizing the uplink SINR \( \tilde{\gamma}_k(\mathcal{K}) \) of the \( k \)-th user is the minimum mean square error (MMSE) filter with fixed \( \{q_k\} \), i.e.,

\[
\mathbf{w}_k^{(s)} = \left( \mathbf{I}_N + \sum_{k \in \mathcal{K}} q_k \mathbf{h}_k \mathbf{h}_k^H \right)^{-1} \mathbf{h}_k, \quad (13)
\]

where \( \mathbf{I}_N \) denotes \( N \)-by-\( N \) identity matrix. For fixed \( \{\mathbf{w}_k\} \), problem (11) is rewritten as

\[
\min_{\kappa, q} \left( \sum_{k \in \mathcal{K}} \kappa_k + g(\kappa) - h(\kappa) \right), \quad \text{s.t.} \quad \tilde{\gamma}_k \kappa_k - q_k |\mathbf{h}_k^H \mathbf{w}_k|^2 + \varphi(\kappa, q) - \phi(\kappa, q) \leq 0, \forall k \in \mathcal{K}, \quad (14a)
\]

where \( \lambda \) penalizes the objective function for any \( \kappa_k \) with its value between 0 and 1. A large value of \( \lambda \) will be helpful for convergence of the algorithm, but may miss some users. Based on the reference [37], a small value (0.01 in Algorithm 1) of \( \lambda \) is chosen to find a better solution in our work.
where \( \varphi_k(\kappa, q) \) and \( \phi_k(\kappa, q) \) are defined as

\[
\varphi_k(\kappa, q) = \frac{1}{2} \left( \tilde{\gamma}_k \kappa_k + \sum_{l \in K, l \neq k} q_l \left| \mathbf{h}_l^H \mathbf{w}_k \right|^2 \right)^2,
\]

(15a)

\[
\phi_k(\kappa, q) = \frac{1}{2} \left( \tilde{\gamma}_k \kappa_k^2 + \frac{1}{2} \sum_{l \in K, l \neq k} q_l \left| \mathbf{h}_l^H \mathbf{w}_k \right|^2 \right)^2.
\]

(15b)

Problem (14) belongs to the class of difference of convex programming problem, since the objective function (14a) and constraint (14b) are two of different convex functions. In the sequel, we resort to the classic SCA-based methods [38].

Using the convexity of functions \( h(\kappa) \) and \( \phi(\kappa, q) \), we have

\[
h(\kappa) = \psi(\kappa) + \sum_{k \in K} h'(\kappa_k)(\kappa_k - \kappa_k^t),
\]

\[
\phi_k(\kappa, q) = \psi_k(\kappa, q) + \sum_{l \in K, l \neq k} \rho_{k,l}(q_l)(q_l - \bar{q}_l(t)).
\]

(16)

where \( h'(\kappa_k) \triangleq 2 \lambda \left( \kappa_k + \sum_{l \in K} \kappa_l \right), \rho_{k,m}(q) \triangleq \left| \mathbf{h}_m^H \mathbf{w}_k \right|^2 \sum_{n \in K, n \neq k} q_n \left| \mathbf{h}_n^H \mathbf{w}_k \right|^2 \), and superscript \( \tau \) is the \( \tau \)-th iteration of the SC-U-CBF algorithm presented shortly. From the aforementioned discussions, the convex approximation problem solved at the \( (\tau + 1) \)-th iteration of the proposed algorithm is given by

\[
\min_{\kappa_k, q_k} - \sum_{k \in K} \kappa_k + g(\kappa) - \psi(\kappa),
\]

(17a)

s.t.

\[
\tilde{\gamma}_k \kappa_k - q_k \left| \mathbf{h}_k^H \mathbf{w}_k \right|^2 + \varphi_k(\kappa, q) - \bar{q}_k(\kappa, q) \leq 0, \forall k \in K,
\]

(17b)

(10b), (10e).

Based on the above mathematical transformation, the SC-U-CBF is summarized in Algorithm 1. In the description of Algorithm 1, \( \delta \) denotes the maximum permissible error, and \( \psi(\tau) \) and \( \zeta(\tau) \) denote the objective value of problem (11) at the \( \tau \)-th iteration and problem (17) at the \( \tau \)-th iteration and the \( \ell \)-th iteration, respectively. Note that SC-U-CBF is also suitable for problem scenarios based on the Shannon capacity formula, as we just need to replace the \( R(\tilde{\gamma}_k) \) with \( C(\tilde{\gamma}_k) \) in problems (5), (6), and (9), and replace the minimum SINR \( \tilde{\gamma}_k \) in problem (10b) for achieving minimum achievable rate \( r_k \) with \( \tilde{\gamma}_k^t = 2^{r_k} - 1 \). The convergence of SC-U-CBF can be guaranteed by the monotonic boundary theory. To speed up the convergence of SC-U-CBF, we can first filter out the users which meets constraints (5b) and (5c) by adopting a single user communication with the maximum ratio transmission (MRT) and full power transmission, thus, at least one user could be scheduled in such circumstance.

**Algorithm 1** The SC-U-CBF Algorithm for Problem (10)

1. Let \( t = 0, \tau = 0, \lambda = 10^{-2}\). Initialize the BF vectors \( \{\mathbf{w}_k^{(0)}\} \) and downlink power vectors \( \{p_k^{(0)}\} \), such that constraint (5b) and (5c) are satisfied.
2. Initialize \( \zeta(0) \) and \( \psi(0) \), calculate the downlink SINR \( \tilde{\gamma}_k \) via \( \{p_k^{(0)}, \mathbf{w}_k^{(0)}\} \) and Eq. (2), and obtain the uplink power vector \( q = [q_1, \cdots, q_K]^T \) with

\[
q = \mathbf{P}^{-1}\mathbf{I}^*_K,
\]

(18)

where \( \mathbf{I}^*_K \) is the all-one vector with \( K^\ast \) dimensions, and matrix \( \mathbf{P} \) is given by

\[
[\mathbf{P}]_{k,l} = \begin{cases}
\left| \mathbf{h}_k^H \mathbf{w}_k \right|^2, k = l, \\
-\left| \mathbf{h}_k^H \mathbf{w}_k \right|^2, k \neq l.
\end{cases}
\]

(19)

3. Let \( t \leftarrow t + 1 \). Solve problem (17) to obtain \( \{\kappa_k(t), \bar{q}_k(t)\} \) and \( \zeta(t) \).
4. If \( \frac{\zeta(t) - \zeta(t-1)}{\zeta(t-1)} \leq \delta \), go to Step 5. Otherwise, go to Step 3.
5. Let \( \tau \leftarrow \tau + 1 \), update \( \{\mathbf{w}_k^{(\tau)}\} \) with \( \{q_k(t)\} \) and Eq. (13), and obtain the objective value \( \psi(\tau) \). If \( \frac{|\psi(\tau) - \psi(\tau-1)|}{\psi(\tau-1)} \leq \delta \), stop iteration and go to Step 6. Otherwise, go to Step 3.
6. Calculate the uplink SINR \( \tilde{\gamma}_k \) via \( \{q_k(t), \mathbf{w}_k^{(\tau)}\} \) and Eq. (7), and obtain the downlink power vector \( p = [p_1, \cdots, p_K]^T \) with

\[
p = \mathbf{D}^{-1}\mathbf{I}^*_K,
\]

(20)

where matrix \( \mathbf{D} \) is given by

\[
[D]_{k,l} = \begin{cases}
\left| \mathbf{h}_k^H \mathbf{w}_k \right|^2, k = l, \\
-\left| \mathbf{h}_k^H \mathbf{w}_l \right|^2, k \neq l.
\end{cases}
\]

(21)

7. Calculate the objective function value, then output the US, PA and BF vectors \( \{\kappa_k, p_k, \mathbf{w}_k\} \).

**A. Problem Transformation and Loss Function Definition**

Different from the proposed SC-U-CBF that alternately updates the BF vectors, in the sequel, it is regarded as intermediate variables about the virtual uplink power vectors. Taking (13) into (8), the uplink received SINR of user \( k \) is rewritten as

\[
\tilde{\gamma}_k = \frac{q_k \left| \mathbf{h}_k^H \mathbf{A}^{-1}\mathbf{h}_k \right|^2}{\sum_{l \neq k, l \in K} q_l \left| \mathbf{h}_l^H \mathbf{A}^{-1}\mathbf{h}_k \right|^2 + \left| \mathbf{A}^{-1}\mathbf{h}_k \right|^2}.
\]

(22)
Algorithm 2 The J-USBF Learning Algorithm

Input: \( D = \{ h_k \} \): Testing sample with \( K \) users;
\( \Theta \): The trainable parameters of JEEPON.
Output: The optimization strategy \( \{ \kappa_k, \chi_k(w_k) \} \) of sample \( D \).
1. Construct graph \( G(\mathcal{V}, \mathcal{E}) \) for sample \( D \) via the graph representation module.
2. Input graph \( G(\mathcal{V}, \mathcal{E}) \) to JEEPON and obtain the US-PA strategy \( \{ \kappa_k, \chi_k(w_k) \} \).
3. Calculate the BF vectors \( \{ w_k \} \) via Eq. (13), and output the strategy \( \{ \kappa_k, \chi_k(w_k) \} \).
4. Calculate the uplink SINR \( \gamma_k \) via \( \{ \kappa_k, \chi_k(w_k) \} \) and Eq. (7), and obtain the downlink power vector \( \{ p_k \} \) via Eq. (21).

where \( \Lambda = I_N + \sum_{k \in K} q_k G_k G_k^H \). Thus, problem (10) is formulated as follows

\[
\begin{align*}
\max_{\{\kappa_k, q_k\}} & \sum_{k \in K} \kappa_k, \\
\text{s.t.} & \quad 0 \leq \kappa_k \leq 1, \forall k \in K, \quad (23a) \\
& \sum_{k \in K} (\kappa_k - \kappa_k^2) \leq 0, \quad (23b) \\
& \kappa_k \gamma_k \leq \gamma_k, \forall k \in K, \quad (23c) \\
& \sum_{k \in K} q_k \leq P, \quad q_k \geq 0, \forall k \in K. \quad (23d)
\end{align*}
\]

To facilitate the design of JEEPON, incorporating partially the constraints into the objective function, the violation-based Lagrangian relaxation method [39] is adopted to formulate problem (23) as an unconstrained optimization problem. Observe the constraints constraints (23b) and (23e) only contain single optimization variables that can be satisfied by subsequent projection-based methods. For constraints (23c) and (23d), we introduce the non-negative Lagrangian multipliers \( \{ \mu, \nu \in \mathbb{R}^+ \} \) to capture how much the constraints are violated. Thus, the partial Lagrangian relaxation function of problem (23) is given by

\[
L = - \sum_{k \in K} \kappa_k + \mu \sum_{k \in K} \chi_k^\gamma (\kappa_k - \kappa_k^2) + \nu \sum_{k \in K} \chi_k (\kappa_k \gamma_k - \gamma_k),
\]

where \( \chi_k^\gamma(x) = \max\{x, 0\} \) is the violation degree function. Further, the Lagrangian dual problem of (23) is formulated as

\[
\max_{\{\mu, \nu\}} \min_{\{\kappa_k, q_k\}} L.
\]

To update the trainable parameters of JEEPON, a primal-dual learning framework (PDLF) is proposed to train it in an unsupervised manner, and the loss function is defined as \( \text{Loss} = L/K \). In the sequel, we focus on describing the architecture of JEEPON and PDLF.

B. Graph Representation and Model Design

After defining loss function, how to construct an effective deep learning model is the key. As stated in the Introduction, conventional DNNs have emerged as an effective tool to solve such challenging radio resource management problems, but may face failure of exploiting the prior topology knowledge in WCNs. Meanwhile, GNNs have shown their ability of exploring the network topology. To this end, GNNs will be adopted in our work. In the sequel, we will first introduce the graph representation method of single-cell WCNs, and then discuss how to design the JEEPON model.

WCNs can be naturally divided into undirected/directed graphs depending on the topology structures, and homogeneous/heterogeneous graphs depending on types of the communication links and user equipments (UEs) [29]. For notational convenience, a graph with node set \( \mathcal{V} \) and edge set \( \mathcal{E} \) is defined as \( G(\mathcal{V}, \mathcal{E}) \), where the node \( v \in \mathcal{V} \) and edge \( e_{u,v} \in \mathcal{E} \) (between node \( u \) and node \( v \)) weight vectors are represented as \( x_u \) and \( e_{u,v} \), respectively. In the graph representation of single-cell cellular networks, we can consider the UEs as nodes and the interfering links between different UEs as edges, as shown in Fig. 1. In general, the node and edge weights of graph \( G(\mathcal{V}, \mathcal{E}) \) mainly include CSI and other environmental information, such as user weights and Gaussian noise. In order to reduce the dimensionality of node and edge weight vectors, we consider using the squared-absolute value of channel vector inner products to represent channel gains and interferences. Therefore, the weights of node \( v \) and edge \( e_{u,v} \) are defined as \( x_v = |h_v|^2 \) and \( e_{u,v} = |h_{u,v}|^2 \), respectively.

Following the completion of the WCN graph representation, we focus on the design of JEEPON to output the US-PA strategy, where the optimization vectors are carefully defined in the representation vector of nodes. Specifically, JEEPON applies a message passing mechanism based graph convolutional network (GCN) [40] to iteratively update the representation vector of node \( v \in \mathcal{V} \) by aggregating weights from its neighbor nodes and edges. The GCN consists of two steps, first generating and collecting messages from the first-order neighborhood nodes and edges of node \( v \), and then updating the representation vector of node \( v \) with the aggregated messages. After \( \ell \) times of graph convolutions, the representation vector of node \( v \) captures the messages within its \( \ell \)-hop neighborhood nodes and edges. To be specific, the update rule of the \( \ell \)-th GCN layer at node \( v \) is formulated as

\[
\begin{align*}
\mathbf{m}^{(\ell)}_{u,v} &= \mathbf{M}^{(\ell)} \left( \beta^{(\ell-1)}_{x_{u,v}} \right), \quad u \in \mathcal{N}_v, \\
\mathbf{g}^{(\ell)}_v &= \mathbf{G} \left( \mathbf{F}_{\text{max}} \left( \left\{ \mathbf{m}^{(\ell)}_{u,v} \right\} \right), \mathbf{F}_{\text{mean}} \left( \left\{ \mathbf{m}^{(\ell)}_{u,v} \right\} \right) \right), \quad v \in \mathcal{V},
\end{align*}
\]

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where $\mathcal{N}_v$ is the first-order neighborhood set of node $v$, $\beta_v^{(l)} \triangleq [\kappa_v, q_v] \in \mathbb{R}^2$ represents the pairwise optimization vector of node $v$ at the $l$-th GCN layer, and $\beta^{(0)}$ is initialized with an all-zero vector. Therefore, when the update of the $l$-th graph convolution operation is completed, the representation vector of node $v$ could be formulated as $[\beta_v^{(l)}, x_v]$. Fig. 2 illustrates the state update process of node $v$ at the $l$-th GCN layer. Here, $\mathcal{M}_v^{(l)}(\cdot)$ is a message construction function defined on each edge to generate edge message $m_{uv}^{(l)} \in \mathbb{R}^m$ by combining incoming node and edge weights, where $m$ is the dimension size. $G(a_1, a_2) = [a_1, a_2]$ is a message aggregation function, which is applied to directly concatenate two vectors $a_1, a_2 \in \mathbb{R}^m$. In our work, the values of $F_{\max}(\{m_{uv}^{(l)}\})$ and $F_{\text{mean}}(\{m_{uv}^{(l)}\})$ are concatenated together and the aggregated message $g_v^{(l)} \in \mathbb{R}^{2m}$ is output using $G(\cdot)$. Here, $F_{\max}(\cdot)$ and $F_{\text{mean}}(\cdot)$ respectively denote the max and mean function. $U_\theta^{(l)}(\cdot)$ is a state update function defined on each node, which is used to update the node representation through the aggregated message $g_v^{(l)}$, node weight $x_v$, and optimization vector $\beta_v^{(l-1)}$. In JEEPON, function $\mathcal{M}_v^{(l)}(\cdot)$ and function $U_\theta^{(l)}(\cdot)$ are parameterized by different neural network modules.

Through the combination of several GCN layers, JEEPON can gather multi-hop node and edge weights. An illustration of JEEPON is given in Fig. 3, which consists of $N_L$ GCN layers and one projection activation (PAC) layer. Each GCN layer includes an input layer, an output layer, and two different MLPs which are composed of linear (LN) layers, batch normalization (BN) layers and activation (AC) layers. In the final part of JEEPON, we utilize the PAC layer to put $\{\kappa_k^{(N_L)}, q_k^{(N_L)}\}$ into the feasible region $\Omega$, i.e.,

$$\Omega \triangleq \{\kappa, q: 0 \leq \kappa \leq 1, \sum_{k \in K} q_k \leq P, q_k \geq 0, \forall k \in K\}. \quad (27)$$

To this end, the projection functions of the PAC layer are defined as

$$\kappa_k^{(s)} = F_{\text{relu}}(\kappa_k, 1), \quad q_k^{(s)} = F_{\text{relu}}(q_k, P), \forall k \in K,$$

$$q_k^{(s)} = \frac{P}{\max\{P, \sum_{k \in K} q_k^{(s)}\}} q_k^{(s)}, \forall k \in K, \quad (28)$$

where function $F_{\text{relu}}(z, b) = \max\{\min\{z, 0\}, b\}$, and $b$ is the upper bound of the input. Furthermore, due to the matrix inversion operation in the uplink SINR equation (22), it leads to a high computational overhead. To speed up the computation, the following Lemma 1 is applied to replace the direct matrix inversion by $K$ matrix iterations. Specifically, it reduces the computational complexity to $\mathcal{O}(KN^2)$ instead of matrix inversion complexity $\mathcal{O}(KN^2 + N^3)$, where $\mathcal{O}(\cdot)$ is the big-O notation for describing the computational complexity.

**Lemma 1:** According to the Sherman-Morrison formula [41], for an invertible square matrix $A \in \mathbb{C}^{N \times N}$, if there exists two column vectors $u, v \in \mathbb{C}^{N \times 1}$, $1 + v^HA^{-1}u \neq 0$, then the inverse of $A$ is given by

$$\begin{align*}
(A + uv^H)^{-1} &= A^{-1} - \frac{A^{-1}uv^HA^{-1}}{1 + v^HA^{-1}u}.
\end{align*} \quad (29)
$$

Based on this formula, let $T_n = \Lambda^{-1} - \frac{\Lambda^{-1}q_n\Lambda^{-1}T_n}{1 + q_n\Lambda^{-1}q_n}$, then $T_n$ can be converted into an iterative matrix product form, which is formulated as follows

$$T_n = \begin{cases}
I_N, & n = 0, \\
T_{n-1} - \frac{q_nT_{n-1}T_n}{1 + q_n\Lambda^{-1}q_n}, & n > 0.
\end{cases} \quad (30)$$

### C. Primal-Dual Learning Framework

With regard to the aforementioned aspects, PDLF is developed for training the JEEPON model to solve the Lagrangian dual problem (25), which is composed of two parts, the primal update part and the dual update part, as shown in Fig. 4. The primal update part takes the user’s historical channel data sample $D \triangleq \{h_k\}$ as input, and outputs the related US-PA strategy $\Phi(D, \Theta) \triangleq \{\kappa_k, q_k\}$, where $\Theta$ is the trainable parameters of JEEPON. Specifically, it includes a graph representation module for WCN topology construction, a JEEPON model for US-PA optimization, and a loss function module for updating $\Theta$. In the dual part, the Lagrangian multipliers $\{\mu, \nu\}$ are updated by the sub-gradient optimization method. PDLF runs two parts alternately, the former minimizes Lagrangian relaxation function $\mathcal{L}$ with fixed $\{\mu, \nu\}$ by updating $\Theta$ to obtain a suitable $\{\kappa_k, q_k, w_k\}$, and the latter maximizes $\mathcal{L}$ with fixed $\{\kappa_k, q_k, w_k\}$ by updating $\{\mu, \nu\}$. Therefore, the update rule of $\{\mu, \nu\}$ at the $\tau$-th epoch is

$$\mu^{(\tau+1)} = \mu^{(\tau)} + \varepsilon_\mu \sum_{k \in K} \chi_k^{\geq} (\kappa_k^{(\tau)} - (\kappa_k^{(\tau)})^2),$$

$$\nu^{(\tau+1)} = \nu^{(\tau)} + \varepsilon_\nu \sum_{k \in K} \chi_k^{\geq} (\kappa_k^{(\tau)} - \gamma_k^{(\tau)}) \quad (31)$$
where $\varepsilon_\mu$ and $\varepsilon_\nu$ is the update step-size of $\mu$ and $\nu$, respectively. In addition, the Lagrangian multipliers are updated every epoch based on the violation degree of the training datasets. For the inner optimization of problem (25), JEEPON is proposed to transform it into a statistical learning problem, which aims to obtain appropriate optimization vectors $\{\kappa_k, q_k\}$ by updating the trainable parameters of JEEPON.

PDLF is designed for training JEEPON. Unlike the penalty-based supervised training method in [25], the proposed PDLF alternately updates $\Theta$ and $\{\mu, \nu\}$ in an unsupervised manner, as summarized in Algorithm 3. Specifically, we generate a training dataset $D \triangleq \{D_i\}_{i=1}^{N_{ts}}$ with $N_{ts}$ samples, and each sample with the same size. The training stage of PDLF lasts for $N_e$ epochs in total. In the primal update part, PDLF first constructs the graph representation for sample $D_i$ (Setp 5), and takes it as the input of JEEPON. Then, JEEPON outputs the US-PA strategy $\Phi(D_i, \Theta) \triangleq \{\kappa_k, q_k\}$ of sample $D_i$ (Step 6), and adopt the loss function module to update $\Theta$ (Step 7). The sub-gradient values of $\{\mu, \nu\}$ are also stored to avoid repeated traversal of the training dataset (Steps 8-10). Therefore, in the dual update part, $\{\mu, \nu\}$ are updated by the recorded dual gradient variables $\{\nabla_{\mu}^{(N_{ts})}, \nabla_{\nu}^{(N_{ts})}\}$ and equation (31) (Step 13).

V. NUMERICAL RESULTS

In this section, numerical results are presented for the joint US-BF optimization problem in the multiuser MISO downlink system. We first introduce the experimental environment and system parameters. Next, the convergence of SCA-USBF and J-USBF is evaluated. Then, the performance of G-USBF, SCA-USBF, and J-USBF is discussed in different system scenarios, as well as the generalizability of J-USBF. In addition, the performance of J-USBF and the convolutional neural network based US-BF (CNN-USBF) algorithm (see Appendix B) are also compared. Finally, the computational complexity of the algorithms is presented and discussed, which clearly validates the speed advantage of J-USBF.

A. Experimental Setup

In the experiment, the $K$ single-antenna users are randomly distributed in the range of $(d_{i_{min}}, d_{i_{max}})$ from the BS, $d_{i_{min}}, d_{i_{max}} \in (d_{min}, d_{max})$, where $d_{min} = 50m$ is the reference distance and $d_{max} = 200m$ denotes the cell radius, as shown in Fig. 5. The channel of user $k$ is modeled as $h_k = \sqrt{\rho_k}H_k \in \mathbb{C}^{N \times 1}$ where $h_k \sim CN(\mathbf{0}, \mathbf{I}_N)$ is the small-scale fading, $\rho = 3$ is the path-loss exponent, and $\rho_k = 1/(1+(d_k/d_{min})^\rho)$ denotes the long-term path-loss between user $k$ and the BS with $d_k$ representing the distance in meters (m). For simplicity, we assume that all users have the same additive noise variance, i.e., $\sigma_k^2 = \sigma^2$, $\forall k \in K$, thus, the signal-to-noise ratio (SNR) is defined as $\text{SNR} = 10\log_{10}(P/\sigma^2)$ in dB.

In the neural network module, J-USBF is implemented by $N_{L} = 2$ GCN layers\textsuperscript{\ref{footnote:GCN}} via Pytorch, and the functions $M_{\theta}(\cdot)$ and $U_{\theta}(\cdot)$ in each GCN layer are parameterized by MLPs with sizes $H_{1}$ and $H_{2}$, respectively. Training and test stages for J-USBF are sequentially implemented. The learing rate of J-USBF and Lagrangian multipliers are set to $\eta = 5 \times 10^{-5}$ and $\varepsilon_\mu, \varepsilon_\nu = 10^{-5}$, respectively. For each configuration, we respectively prepare $N_{ts} = 5000$ training samples and $N_{te} = 1000$ testing samples.

\textsuperscript{\ref{footnote:GCN}}Note that the GCN layer number is set with experimental experience.
The training stage lasts for $N_e$ epochs. The entire training stage lasts for $N_e = 200$ epochs. According to the conclusion in [21, Corollary 1], the user minimum achievable SINR $\gamma_k$ will be set by the system parameters $(D, n, \epsilon)$. Note that unless mentioned otherwise, the experiments adopt the default system parameters in Table I.

### B. Convergence Analysis of SCA-USBF and J-USBF

The convergence of SCA-USBF and J-USBF is evaluated in this section, where part of the system parameters are set to $K = 50$ and $(d_l, d_r) = (60m, 100m)$. Fig. 6(a) illustrates the objective value curve of SCA-USBF for different random channel realizations, indicating that SCA-USBF can reach the convergence state through iterations. Fig. 6(b) illustrates the objective value curve of J-USBF during the training stage, where the objective value of the training samples varies in the range (light blue line), and the average objective value curve (blue line) converges as the number of iterations increases to $3.5 \times 10^7$. During the testing stage, the constraint violation ratios of J-USBF for different testing samples are shown in Table II. It is observed that the percentage of illegal results is $2.26\%$, which is much lower than the results satisfying the constraints. Note that the value of $\kappa_k$, $\forall k \in K$ will be set to 1 if $0 < \kappa_k < 1$ is obtained, and all the scheduled users are filtered again with the per-user minimum SINR requirement.

### C. Performance and Generalizability Evaluation

In this subsection, the performance of J-USBF, SCA-USBF and G-USBF with different system parameters are evaluated and compared. For intuitive comparison, the obtained results of SCA-USBF and J-USBF are normalized by the results of G-USBF, defined as $R_1 = \frac{N_S}{N_G} \times 100\%$ and $R_2 = \frac{N_J}{N_G} \times 100\%$, where $N_S$, $N_J$ and $N_G$ are the average number of scheduled users obtained through SCA-USBF, J-USBF and G-USBF, respectively. In addition, we also define the result percentage of CNN-USBF and J-USBF as $R_3 = \frac{N_C}{N_G} \times 100\%$, where $N_C$ is the number of scheduled users obtained through CNN-USBF.

**1) Performance With Various $K$ and $(d_l, d_r)$:** This experiment investigates the influences of $K$ and $(d_l, d_r)$ and compares the performance of J-USBF with G-USBF and SCA-USBF, as well as with CNN-USBF in large-scale user scenarios. Table III shows that when $K$ is small, the performance of J-USBF is closer to that of G-USBF, because sufficient system resources are conducive to model optimization. J-USBF remains stable when $K$ changes from 20 to 50, and there exist only 2.56% performance degradation at most. Besides, the performance gain of J-USBF improves with the distance interval changes from 20m to 40m, since the smaller distance interval leads to the lack of diversity for each user, which brings more difficulties to the learning of J-USBF. In Fig. 7, we show the average performance of these three algorithms with different $(d_l, d_r)$. It suggests that J-USBF could achieve a more stable and closer performance compared with G-USBF as $(d_l, d_r)$ increases. Owing to the fact that the number of scheduled users is reduced with the increase of $(d_l, d_r)$, and the obtained results are more homogeneous, which is beneficial to the learning of J-USBF.

Considering large-scale user scenarios, we focus on the performance comparison of J-USBF and CNN-USBF, whereas ignoring G-USBF and SCA-USBF due to the high computational overhead. Table IV shows that the performance gap between CNN-USBF and J-USBF widens as $K$ increases, especially when $K = 200$ and $(d_l, d_r) = (60m, 100m)$, the performance of the former can only reach 87.36% of the latter. This indicates that incorporating WCN topology information into model learning is helpful for performance improvement and stability maintenance.

**2) Performance With Various SNR Settings:** This experiment compares the performance of J-USBF, SCA-USBF and

---

**TABLE I**

| Parameters          | Values |
|---------------------|--------|
| Range of SNR        | 10 dB  |
| Blocklength $n$     | 128    |
| Decoding error probability $\epsilon$ | $10^{-6}$ |
| Transmission data bits $D$ | 256 bits |
| BS antenna number $N$ | 32     |
| Number of candidate users $K$ | 30     |
| Maximum permissible error $\delta$ | 10% |

**TABLE II**

| Different constraint situations | Percentage of total samples |
|---------------------------------|-----------------------------|
| $\kappa_k = 0, q_k \geq 0, \forall k \in K$ | 75.436% |
| $0 < \kappa_k < 1, q_k \geq 0, \forall k \in K$ | 2.264% |
| $\kappa_k = 1, \gamma_k > \gamma_k, \forall k \in K$ | 0.004% |
| $\kappa_k = 1, \gamma_k \leq \gamma_k, \forall k \in K$ | 22.296% |

---

Fig. 6. The objective value curves of SCA-USBF and J-USBF.

Fig. 7. Average number of scheduled users with various $(d_l, d_r)$. 
G-USBF with different SNR settings, and the obtained results are summarized in Table V. It is observed that J-USBF achieves competitive performance (larger than 90.77%) with SNR = 5 dB, while SCA-USBF maintains over 95.73% near-optimal performance compared with G-USBF. Although the performance gap of J-USBF is enlarged as \( K \) increase, the trend of degradation is rather slow. For the configuration SNR = 15 dB and \((d_l, d_r) = (50m, 100m)\), J-USBF obtains only a 1.78% relative performance gap with G-USBF when \( K \) changes from 20 to 50. Even when \((d_l, d_r) = (100m, 150m)\), J-USBF still maintains a stable performance. Moreover, Fig. 8 illustrates the gap between the SCA-USBF and J-USBF increases while SNR changes from 0 dB to 20 dB. With the increase of SNR, channel condition becomes better and more users might meet the requirement of QoS. Therefore, the solution space for problem (5) enlarges and SCA-USBF shows its advantages under this condition, because it obtains optimal/suboptimal results. On the other hand, J-USBF is difficult to capture the optimal value as the solution space increases in such circumstance. However, the gap between the SCA-USBF and J-USBF decreases when SNR changes from 20 dB to 30 dB, since much better channel condition is sufficient for serving all the users.

3) Performance With Various SINR Requirements: The ultimate scheduling results of the investigated problem are significantly affected by the per-user minimum SINR requirement, where value \( \gamma = F_\gamma(D, n, \epsilon) \) is obtained with different system parameters \( D, n \), and \( \epsilon \), and the results are summarized in Table VI. From the table, it is observed that the average performance of J-USBF remains above 88.97% compared with G-USBF under different SINR requirements and user distribution distances. However, one needs to point out that with the reduction of SINR requirements, the performance improvement of J-USBF is lower than G-USBF, especially when \((d_l, d_r) = (60m, 80m)\). Therefore, J-USBF shows a slight performance degradation compared with G-USBF when the SINR requirement is reduced, while the performance improvement of SCA-USBF increases at the same time.

4) Generalizability With Various User Distributions: Generalizability is another critical evaluation property for J-USBF, and it focuses on investigating whether the trained network model has the ability to perform well in unknown WCN scenarios. To test the generalizability, J-USBF is trained from a certain scenario whose system parameters are different from the test ones. Specifically, J-USBF is trained with \((d_l, d_r) = (100m, 120m)\), then the trained model is applied to the test scenarios with different \((d_l, d_r)\), without any further training\(^1\). Table VII shows comparison results of G-USBF and J-USBF, where \( R_4 = \frac{N_{JUSBF}}{N_{USBF}} \times 100\% \) represents the average performance of J-USBF normalized by G-USBF and \( N_{JUSBF} \) is the average number of scheduled users using J-USBF. Form the table, it is observed that J-USBF performs well over the neighboring user distribution distances when the test distance interval is 40m. Moreover, when \((d_l, d_r) = (80m, 100m)\) and there is no intersection with \((100m, 120m)\), the performance of J-USBF is still acceptable at \( K = 10 \). Based on the aforementioned analysis, our proposed J-USBF can be well generalized to scenarios with neighboring user distribution distances.

D. Computational Complexity Analysis

In this subsection, the computational complexity of G-USBF, SCA-USBF and J-USBF is analyzed and compared. Considering the differences in implementation platforms and algorithm design languages, we count the floating-point computation of the proposed algorithms. Firstly, G-USBF includes the US optimization and BF design, whose floating-point computation is about \( \sum_{k=2}^{\hat{k}} 4(K - \hat{k} + 1)(I_1(\hat{k}^3 N + 5k^2 N) + \hat{k}^2) \), where \( \hat{k} \) and \( I_1 \) represent the number of scheduled users and iterations, respectively. Secondly, SCA-USBF includes the inner and outer optimizations, whose floating-point computation is about \( 4I_2(I_2(7K^2 N + 4KN + 14K^2) + K(N^3 + 2N^2 + 2N)) \), where \( I_2 \) and \( I_3 \) represent the number of iterations for both parts. For J-USBF, since the JEEPON model is trained offline, we mainly consider the computation of the testing stage, including the graph representation module, the GCN.

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**Table III**

| \( K \) | \( R_1 \) and \( R_2 \) with varying \((d_l, d_r)\) |
|---------|---------------------------------|
|         | \( (50m, 70m) \) | \( (60m, 80m) \) | \( (50m, 90m) \) | \( (60m, 100m) \) |
| 10      | 100%    | 95.68% | 99.98% | 94.70% | 100% | 93.94% | 99.89% | 93.41% |
| 20      | 99.67%  | 90.04% | 99.64% | 91.35% | 99.52% | 92.02% | 99.22% | 92.32% |
| 30      | 99.94%  | 89.68% | 99.63% | 90.33% | 98.80% | 90.57% | 98.77% | 91.25% |
| 40      | 99.86%  | 88.91% | 99.54% | 89.86% | 98.52% | 90.27% | 98.24% | 91.08% |
| 50      | 99.84%  | 88.15% | 98.73% | 88.79% | 97.48% | 89.46% | 97.10% | 90.15% |

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**Table IV**

| \( K \) | \( R_3 \) with varying \((d_l, d_r)\) |
|---------|---------------------------------|
|         | \( (50m, 70m) \) | \( (60m, 80m) \) | \( (50m, 90m) \) | \( (60m, 100m) \) |
| 50      | 93.06%  | 96.26% | 92.42% | 93.95% |
| 100     | 92.89%  | 90.83% | 91.42% | 90.80% |
| 150     | 89.14%  | 90.53% | 90.59% | 89.46% |
| 200     | 88.75%  | 88.38% | 87.51% | 87.36% |
module and the SINR module. For simplicity, we assume that the GCN module is composed by MLPs with the dimensions $\mathcal{H} = \{h_i\}$. Therefore, the floating-point computation of J-USBF is about $2(2K^2N + 2KN^2 + K \sum_{i=1}^{L} \sum_{j=1}^{N} (2 + h_{\ell,j-1})h_{\ell,j})$. For intuitive comparison, Fig. 9 illustrates the comparison of the floating-point computational magnitude of each algorithm for different number of users and iterations, where $x$-axis and $y$-axis respectively represent the iteration of algorithm and user number, and $z$-axis represents complexities with logarithmic coordinate. The computational magnitude of J-USBF is lower than that of G-USBF and

| SNR(dB) | $K$ | $R_1$ and $R_2$ with varying $(d_l, d_r)$ |
|---------|-----|------------------------------------------|
|         |     | (60m, 90m) | (90m, 120m) | (50m, 100m) | (100m, 150m) |
| 5       | 10  | 98.96%    | 92.13%    | 98.43%    | 94.50%    | 99.37%    | 92.56%    | 97.74%    | 93.17%    |
|         | 20  | 98.22%    | 91.08%    | 97.82%    | 92.43%    | 98.82%    | 91.15%    | 96.59%    | 92.03%    |
|         | 30  | 97.17%    | 90.77%    | 96.58%    | 91.04%    | 97.75%    | 90.83%    | 95.73%    | 91.66%    |
| 15      | 20  | 99.99%    | 90.15%    | 99.60%    | 90.69%    | 100%      | 90.48%    | 99.17%    | 91.15%    |
|         | 30  | 99.87%    | 89.20%    | 99.61%    | 89.78%    | 99.97%    | 89.52%    | 98.46%    | 90.60%    |
|         | 50  | 99.64%    | 88.34%    | 99.55%    | 89.06%    | 99.80%    | 88.70%    | 97.36%    | 89.94%    |

Fig. 8. Performance of the algorithms with various SNR settings.

| $F_\gamma(D, n, c)$ | $\bar{\gamma}$ | $R_1$ and $R_2$ with varying $(d_l, d_r)$ |
|---------------------|-----------------|------------------------------------------|
| (256, 256, 10^{-6})| 1.633           | 99.92%    | 88.97%    | 99.96%    | 90.36%    | 99.97%    | 89.82%    | 99.91%    | 91.03%    |
| (256, 128, 10^{-6})| 5.054           | 99.63%    | 90.33%    | 98.30%    | 91.87%    | 98.77%    | 91.25%    | 98.36%    | 92.78%    |
| (256, 96, 10^{-6})  | 9.291           | 96.41%    | 90.79%    | 94.22%    | 92.94%    | 95.84%    | 91.84%    | 95.38%    | 93.62%    |
| (256, 64, 10^{-6})  | 27.97           | 95.58%    | 91.05%    | 93.95%    | 93.05%    | 94.55%    | 92.76%    | 94.19%    | 94.08%    |

Fig. 9. Comparison of the floating-point computational magnitude of each algorithm for different number of users and iterations.

| $K$ | $N_3$ and $R_4$ with varying $(d_l, d_r)$ |
|-----|------------------------------------------|
|     | (100m, 120m) | (80m, 100m) | (80m, 120m) | (100m, 140m) |
|     | $N_3$ | $R_4$ | $N_3$ | $R_4$ | $N_3$ | $R_4$ | $N_3$ | $R_4$ |
| 10  | 5.068 | 94.97% | 7.564 | 84.78% | 6.36 | 91.86% | 4.394 | 92.13% |
| 20  | 6.24 | 93.92% | 8.518 | 84.93% | 7.496 | 89.58% | 5.068 | 91.46% |
| 30  | 5.924 | 92.69% | 9.054 | 83.94% | 8.16 | 88.31% | 5.372 | 88.16% |
| 40  | 6.038 | 91.24% | 9.304 | 82.75% | 8.508 | 87.92% | 5.608 | 87.73% |
| 50  | 6.15 | 90.80% | 9.548 | 83.04% | 8.818 | 85.87% | 5.782 | 86.09% |
SCA-USBF, which indicates its computational efficiency advantage.

VI. CONCLUSION

In this paper, the joint US-BF optimization problem is studied for the multiuser MISO downlink system. Specifically, with the help of uplink-downlink duality theory and mathematical transformations, we formulate the original problem into a convex optimization problem, and propose the G-USBF, SCA-USBF and the J-USBF. Numerical results show that J-USBF achieves close performance and higher computational efficiency. Additionally, the proposed J-USBF also enjoys the generalizability in dynamic WCN scenarios. For future directions, solving the problem of unbearable CSI acquisition burden and signaling overhead caused by the instantaneous perfect CSI applied in this work is interesting and meaningful. Deep learning based resource allocation algorithm needs to be redesigned, and statistical CSI may be helpful to achieve the goal.

APPENDIX A

DESIGN OF THE G-USBF ALGORITHM

In this appendix, the G-USBF algorithm is proposed to slope problem (5), which is inspired by the work in [45] and the near-far effect of WCNs. The feasibility problem in reference [21, problem (35)] forms the basis of G-USBF, which is formulated as follows

$$
\min_{\{w_k\} \in \mathcal{S}} \sum_{k \in \mathcal{S}} \|w_k\|^2, \quad (32a)
$$

subject to

$$
r_k \leq R(\gamma_k), \quad (32b)
$$

where $w_k \in \mathbb{C}^{N \times 1}$ is the BF vector of user $k$, and its downlink power is denoted as $p_k = \|w_k\|^2$. Solving problem (32) can be used to determine whether the scheduled user set $S$ is feasible, i.e., the user rate constraint and the BS power budget need to be satisfied. G-USBF is designed with two stages, namely, the conventional greedy search stage and the user set optimization stage, as summarized in Algorithm 4. Here, G-USBF expands the scheduled user set $S$ from the candidate user set $\mathcal{K}$ in the first stage, and then optimizes $S$ in the second stage to achieve the goal of scheduling more users. Since the G-USBF algorithm has close performance and lower computational complexity compared with the exhaustive search algorithm, therefore, it is used as the baseline.

Algorithm 4 The G-USBF Algorithm for Problem (5)

1. Input candidate user set $\mathcal{K}$ and user CSI $\{h_k\}$, and initialize scheduled user set $S = \emptyset$.
2. Sort the user channels of $\mathcal{K}$ from good to bad via the MRT method, and add the top-ranked user to $S$.
3. In the greedy search stage, move one user from $\mathcal{K}$ to $S$ in sequence without repetition, and obtain temporary user sets with $|\mathcal{K}\setminus S|$ groups.
4. For each temporary user set, solve problem (32) to obtain $\{p_k, w_k\}$, and preserve the user set $S_1^{(s)}$ with the smallest required power.
5. Let $\mathcal{K} \leftarrow \mathcal{K}\setminus S_1^{(s)}, S \leftarrow S_1^{(s)}$ if $\mathcal{K} \neq \emptyset$ and $\sum_{k \in S} p_k \leq P$ is obtained, then go to step 3. Otherwise, go to step 6.
6. In the user set optimization stage, move one user with the largest power consumption from $S$ to $\mathcal{K}$, and obtain the user set $S_2$.
7. Let $S \leftarrow S_2$ and run the greedy search again to obtain a new user set $S_2^{(s)}$. If $|S_1^{(s)}| = |S_2^{(s)}|$, stop iteration then output $S_2^{(s)}$ and $\{p_k, w_k\}$. Otherwise, let $S \leftarrow S_2^{(s)}$ and go to step 6.

APPENDIX B

DESIGN OF THE CNN-USBF ALGORITHM

In this appendix, the CNN-USBF algorithm is proposed to slope problem (23), which is inspired by the work in [46]. In particular, CNN-USBF takes the WCN graph representation as input and outputs the US-PA optimization strategy and BF vectors. To be specific, the update rule of CNN-USBF for node $v$ in graph $G(V, E)$ is formulated as

$$
\text{Input} : D_v^{(0)} = [x_v, F_{\max}([e_{u,v}, f_{\text{mean}}([e_{u,v}])]), u \in \mathcal{N}_v],
$$

CNN : $D_v^{(j)} = F_{\text{std}}(\text{Cov1d}(D_v^{(i-1)})), i = 1, 2, \ldots, N_1$,

DNN : $D_v^{(i)} = F_{\text{std}}(\text{LNN}(D_v^{(i-1)})), i = N_1 + 1, \ldots, N_1 + N_2$,

Output : $D_v^{(N_2)} = [k_v^{(s)}, q_v^{(s)}], \quad (33)$

where $\mathcal{N}_1$ and $\mathcal{N}_2$ denote the layers of CNN and DNN, respectively. $D_v^{(0)}$ is the weights of node $v$ and its neighborhood edges, $D_v^{(N_2)}$ is the US-PA strategy of node $v$, and $F_{\text{std}}(z) = F_{\text{AC}}(F_{\text{BN}}(z))$ is the standardization function used to standardize the network input to accelerate training process and reduce generalization error, which is implemented by BN and AC layers. The neural network module of CNN-USBF is constructed through CNN and DNN, which are implemented and trained by Pytorch and PDLF, respectively. The algorithm steps of CNN-USBF refer to J-USBF. Note that unless mentioned otherwise, the neural network structure of CNN-USBF may also be applicable.

11 Besides the applied GNN and CNN in the paper, other neural networks may also be applicable.
refer to Table VIII and is trained separately for different WCN scenarios.

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REFERENCES

[1] Y. Xu, G. Gui, H. Gacanin, and F. Adachi, “A survey on resource allocation for 5G heterogeneous networks: Current research, future trends, and challenges,” IEEE Commun. Surveys Tuts., vol. 23, no. 2, pp. 668–695, 2nd Quart., 2021.

[2] S. He et al., “A survey of millimeter-wave communication: Physical-layer technology specifications and enabling transmission technologies,” Proc. IEEE, vol. 109, no. 10, pp. 1666–1705, Oct. 2021.

[3] S. He, Y. Huang, L. Yang, B. Ottersten, and W. Hong, “Energy efficient coordinated beamforming for multi-cell system: Duality-based algorithm design and massive MIMO transition,” IEEE Trans. Commun., vol. 63, no. 12, pp. 4920–4935, Dec. 2015.

[4] X. Yu, Y. Du, X. Y. Dang, S.-H. Leung, and H. Wang, “Power allocation schemes for uplink massive MIMO system in the presence of imperfect CSI,” IEEE Trans. Signal Process., vol. 68, pp. 5968–5982, 2020.

[5] H. A. Ammar, R. Adve, S. Shahbazpanahi, G. Boudreau, and K. V. Srinivas, “Distributed resource allocation optimization for user-centric cell-free MIMO networks,” IEEE Wireless Commun., vol. 21, no. 5, pp. 3099–3115, May 2022.

[6] G. Dimic and N. D. Sidirooulos, “On downlink beamforming with greedy user selection: Performance analysis and a simple new algorithm,” IEEE Trans. Signal Process., vol. 53, no. 10, pp. 3857–3868, Oct. 2005.

[7] J. Zhang, R. Chen, J. G. Andrews, A. Ghosh, and R. W. Heath, Jr., “Networked MIMO with clustered linear precoding,” IEEE Trans. Wireless Commun., vol. 8, no. 4, pp. 1910–1921, Apr. 2009.

[8] Q. Shi, M. Razaviyayn, Z.-Q. Luo, and C. He, “An iteratively weighted MMSE approach to distributed sum-utility maximization for a MIMO interfering broadcast channel,” IEEE Trans. Signal Process., vol. 59, no. 9, pp. 4331–4340, Sep. 2011.

[9] G. Dong, H. Zhang, S. Jin, and D. Yuan, “Energy-efficiency-oriented joint user association and power allocation in distributed massive MIMO systems,” IEEE Trans. Veh. Technol., vol. 68, no. 6, pp. 5794–5808, Jun. 2019.

[10] W. Yu and T. Lan, “Transmitter optimization for the multi-antenna downlink with per-antenna power constraints,” IEEE Trans. Signal Process., vol. 55, no. 6, pp. 2646–2660, Jun. 2007.

[11] H. Huh, A. M. Tulino, and G. Caire, “Network MIMO with linear zero-forcing beamforming: Large system analysis, impact of channel estimation, and reduced-complexity scheduling,” IEEE Trans. Inf. Theory, vol. 58, no. 5, pp. 2911–2934, May 2012.

[12] C. Huang et al., “Hybrid beamforming for RIS-empowered multi-hop terahertz communications: A DRL-based method,” in Proc. IEEE Globecom Workshops (GC Wkshps), Dec. 2020, pp. 1–6.

[13] C. Huang et al., “Multi-hop RIS-empowered terahertz communications: A DRL-based hybrid beamforming design,” IEEE J. Sel. Areas Commun., vol. 39, no. 6, pp. 1665–1678, Jun. 2021.

[14] B. Fu, Y. Xiao, H. J. Deng, and H. Zeng, “A survey of cross-layer designs in wireless networks,” IEEE Commun. Surveys Tuts., vol. 16, no. 1, pp. 110–126, 1st Quart., 2014.

[15] A. Goldsmith, “On the optimality of multiantenna broadcast scheduling using zero-forcing beamforming,” IEEE J. Sel. Areas Commun., vol. 24, no. 3, pp. 528–541, Mar. 2006.

[16] C. Chen, W. Cai, X. Cheng, L. Yang, and Y. Jin, “Low complexity beamforming and user selection schemes for 5G MIMO-NOMA systems,” IEEE J. Sel. Areas Commun., vol. 35, no. 12, pp. 2708–2722, Dec. 2017.

[17] C. Zhang, Y. Huang, Y. Jing, S. Jin, and L. Yang, “Sum-rate analysis for massive MIMO downlink with joint statistical beamforming and user scheduling,” IEEE Trans. Wireless Commun., vol. 16, no. 4, pp. 2181–2194, Apr. 2017.

[18] C. E. Shannon, “A mathematical theory of communication,” Bell Syst. Tech. J., vol. 27, no. 3, pp. 379–423, Jul. 1948.

[19] A. A. Nasir, H. D. Tuan, H. H. Nguyen, M. Debbah, and H. V. Poor, “Resource allocation and beamforming design in the short blocklength regime for URLLC,” IEEE Trans. Wireless Commun., vol. 20, no. 2, pp. 1321–1335, Oct. 2020.

[20] Y. Polyanisky, H. V. Poor, and S. Verdú, “Channel coding rate in the finite blocklength regime,” IEEE Trans. Inf. Theory, vol. 56, no. 5, pp. 2307–2359, May 2010.

[21] S. He, Z. An, J. Zhu, J. Zhang, Y. Huang, and Y. Zhang, “Beamforming design for multiuser uRLLC with finite blocklength transmission,” IEEE Trans. Wireless Commun., vol. 20, no. 12, pp. 8096–8109, Jun. 2021.

[22] D. Bertsekas, A. Nedic, and A. Ozdaglar, Convex Analysis and Optimization. Athena Scientific, 2003.

[23] C. She et al., “A tutorial on ultra-reliable and low-latency communications in 6G: Integrating domain knowledge into deep learning,” Proc. IEEE, vol. 109, no. 3, pp. 204–246, Mar. 2021.

[24] Y. Li, S. Han, and C. Yang, “Multicell power control under rate constraints with deep learning,” IEEE Trans. Wireless Commun., vol. 20, no. 12, pp. 7813–7825, Dec. 2021.

[25] W. Xia, G. Zheng, Y. Zhu, J. Zhang, J. Wang, and A. P. Petropulu, “A deep learning framework for optimization of MISO downlink beamforming,” IEEE Trans. Commun., vol. 68, no. 3, pp. 1866–1880, Mar. 2020.

[26] A. Kaushik, M. Alizadeh, O. Waqar, and H. Tabassum, “Deep unsupervised learning for generalized assignment problems: A case-study of user-association in wireless networks,” in Proc. IEEE Int. Conf. Commun. Workshops (ICC Workshops), Jun. 2021, pp. 1–6.

[27] F. Liang, C. Shen, W. Yu, and F. Wu, “Towards optimal power control via ensemble deep neural networks,” IEEE Trans. Commun., vol. 68, no. 3, pp. 1760–1776, Mar. 2020.

[28] T. Chen, X. Zhang, M. You, G. Zheng, and S. Lambotharan, “A GNN-based supervised learning framework for resource allocation in wireless IoT networks,” IEEE Internet Things J., vol. 9, no. 3, pp. 1712–1724, Feb. 2022.

[29] S. He et al., “An overview on the application of graph neural networks in wireless networks,” IEEE Open J. Commun. Soc., vol. 2, pp. 2547–2565, 2021.

[30] W. Cui, K. Shen, and W. Yu, “Spatial deep learning for wireless scheduling,” IEEE J. Sel. Areas Commun., vol. 37, no. 6, pp. 1248–1261, Jun. 2019.

[31] M. Eisen and A. Ribeiro, “Optimal wireless resource allocation with random edge graph neural networks,” IEEE Trans. Signal Process., vol. 68, pp. 2797–2791, 2020.

[32] Y. Shen, Y. Shi, J. Zhang, and K. B. Letaief, “A graph neural network approach for scalable wireless power control,” in Proc. IEEE Global Commun. Conf. (GLOBECOM) Workshops, Dec. 2019, pp. 1–6.

[33] Y. Shen, Y. Shi, J. Zhang, and K. B. Letaief, “Graph neural networks for scalable radio resource management: Architecture design and theoretical analysis,” IEEE J. Sel. Areas Commun., vol. 39, no. 1, pp. 101–115, Jan. 2021.

[34] S. He, S. Xiong, W. Zhang, Y. Yang, J. Ren, and Y. Huang, “GBLinks: GNN-based beam selection and link activation for ultra-dense D2D mmWave networks,” IEEE Trans. Commun., vol. 70, no. 5, pp. 3451–3466, May 2022.

[35] H. Du, Y. Deng, J. Xue, D. Meng, Q. Zhao, and Z. Xu, “Robust online CSI estimation in a complex environment,” IEEE Trans. Wireless Commun., vol. 21, no. 10, pp. 8322–8336, Oct. 2022.

[36] M. Schubert and H. Boche, “Solution of the multiuser downlink beamforming problem with individual SINR constraints,” IEEE Trans. Veh. Technol., vol. 53, no. 1, pp. 18–28, Jan. 2004.

[37] F. Chi, H. D. Tuan, and H. H. Nguyen, “Joint optimization of cooperative beamforming and relay assignment in multi-user wireless relay networks,” IEEE Trans. Wireless Commun., vol. 13, no. 10, pp. 5481–5495, Oct. 2014.
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