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RESEARCH ARTICLE

Deep Learning Based Decentralized Beamforming Methods for Multi-Antenna Interference Channels

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ABSTRACT This paper develops deep learning (DL) based beamforming approaches for multi-antenna interference channels where several base stations (BSs) individually optimize their own beamforming vectors in a decentralized manner. By exploiting the optimal beam structure, we propose an efficient method for beam decisions and coordination among BSs based solely on local information. Moreover, we show that the proposed approach allows a scalable design with respect to the number of users. We also present novel training strategies for the proposed deep neural networks, validating its potential as an innovative decentralized beamforming methodology. Consequently, the proposed DL based decentralized beamforming framework can achieve various optimal beamforming strategies. Numerical results demonstrate the advantages of the proposed framework over conventional methods.

INDEX TERMS Deep learning, decentralized beamforming, interference channel.

I. INTRODUCTION

Multi-antenna signal processing has become essential for wireless communications systems owing to its ability of enhancing the channel capacity [1]. For decades, there have been intensive studies for multiple-input multiple-output (MIMO) transceiver optimization in multi-user systems [2], [3], interference channels (ICs) [4], [5], [6], [7], [8], and multi-cell multi-user networks [9], [10], [11], [12]. However, most works considered a centralized system, which requires a central unit for coordination, and research on decentralized MIMO signal processing algorithms remain insufficient. In this paper, we present a novel decentralized beamforming optimization based on deep learning (DL) framework.

A. MOTIVATION

For future wireless networks, it is desirable to adopt a decentralized multi-antenna signal processing algorithm at individual base stations (BSs) which determines their beamforming policies based only on local channel state information (CSI) [5], [6], [9]. However, the local CSI may result in a performance loss compared to centralized approaches that optimize MIMO transceivers based on all CSI collected from the BSs. In [9], the weighted minimum mean-squared-error (WMMSE) solution was offloaded to individual BSs with the help of interaction between BSs and users. The decentralized beamforming methods in [5] and [6] employed iterative exchanges of information among BSs through backhaul coordination channels, leading to high communication overheads and computation latency.

Furthermore, the variety of services in future wireless networks requests the manageability which can control the throughput of individual devices according to their desired quality-of-service (QoS) levels. This issue can be addressed in line of the Pareto optimal beamforming methods [6], [13], [14], [15]. At the Pareto optimal boundary of the achievable rate region, increasing the rate of a certain device must sacrifice the performance of others. Thus, the complete

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characterization of the Pareto optimal rate tradeoff enables us to design optimized networks consisting of devices with heterogeneous QoS requirements.

Multi-antenna techniques identifying the Pareto optimal rate tradeoff have been studied in multi-cell systems [6], [13], [14], [15] by determining a proper beamforming solution that satisfies arbitrary QoS requirements. Such a task can be formulated as the weighted sum-rate (WSR) maximization [9], [15], [16] and the weighted minimum rate (WMR) maximization [17], [18]. However, most of these works have been confined to the centralized architecture. Although a decentralized beamforming optimization algorithm with the guaranteed Pareto optimality was also presented in [6], its iterative procedure poses excessive backhaul communication overhead.

B. RELATED WORKS

Recently DL techniques have been extensively applied to address the aforementioned challenges. Research has revealed that deep neural networks (DNNs) can shift the calculations of optimization algorithms to the offline training phase. As the real-time inference of trained DNNs can be implemented by simple matrix multiplications, iterative computation steps of beamforming optimization algorithms can be avoided.

DL-based beamforming strategies have been proposed for various network configurations such as single user multiple-input single-output (MISO) systems [19], multi-user broadcasting channels [20], [21], [22], [23], [24], [25], and multi-cell networks [26], [27], [28]. DL models were trained to yield efficient beamforming vectors that enhance the performance while reducing complexity compared to traditional beamforming algorithms [19], [20]. However, a direct beamforming learning (DBL) strategy [20] may be inefficient in large networks as the output dimension of the DNNs should scale up with the network size. These difficulty has been resolved by the feature learning methods [21], [22], [23], [24], [26], [27], [28] which inject the expert knowledge about the optimal beamforming solutions into a design of DNN models. Instead of learning complex beam weights directly, these approaches aim at producing low-dimensional sufficient statistics of the optimal beamforming, which is referred to as *beam features*. These model-driven learning approach enables lightweight DNN architectures and results in improved performance compared to native DBL methods.

Albeit their successes, existing works have been restricted to a centralized DL policy which collects CSI from all BSs for the training and execution of DNNs. Such a strategy is particularly infeasible for multi-cell systems where multi-antenna BSs are separated over the network and can only get access to local CSI. Recently, there have been several studies on establishing decentralized DNN models for resource management problems of distributed wireless devices [29], [30], [31]. A key enabler of the decentralized learning strategy is to split the central DNN unit into several component DNNs to be installed at individual BSs. These DNN modules are designed to process local CSI inputs only and are trained to take solutions of associated BSs. To further improve the performance, the exchange of communication messages generated by neighboring DNN units can be allowed so that the BSs can get the knowledge of others.

These approaches have been extended for decentralized beamforming optimization tasks using the graph neural network (GNN) frameworks [25], [28], [32], [33]. Energy-efficient beamforming solutions for single-cell MISO systems were considered in [25], which facilitates decentralized coordination among multiple users. By doing so, the resulting GNN becomes scalable to the number of users. However, these works are based on the single-cell system model and cannot be extended to the multi-cell networks. In multi-cell systems, [32] presents a GNN-based algorithm for decentralized beamforming in multi-user MISO IC that utilizes dedicated DNNs for both local beam decision-making and coordination processes. Such features have been investigated for MIMO intelligent reflecting surfaces [33] and cell-free MIMO systems [28]. However, existing GNN models invoke multiple backhaul uses among BSs and users due to recursive computational architectures, and thus would need intensive overhead and latency.

C. CONTRIBUTIONS AND ORGANIZATION

In this paper, we propose a decentralized learning framework for identifying the beamforming strategy that improves the achievable rate-region trdeoff of multi-user MISO IC networks. Unlike existing learning-based beamforming optimization techniques [20], [21], [22], [23], [24], [25] which are confined to the single-cell system, our paper considers multi-cell setup. We assume that each BS can only get its local channel information. To execute centralized beamforming DNNs backhaul signaling overheads become prohibitive. This necessitates the development of a novel decentralized learning approach where individual DNNs installed at BSs determine their beamforming vectors based only on limited information sharing.

First, we determine the Pareto optimal rate tradeoff based on arbitrary QoS requirements. Inspired by the Pareto optimal beamforming solution [6], a feature learning architecture is newly presented where a DNN learns sufficient statistics for creating the optimal beamforming vectors. The Lagrange duality analysis of the MISO IFC problem reveals that the optimal beamforming vector can be retrieved from two distinct beam features, namely interference temperature (IT) constraints and dual variables. These features are respectively obtained by dedicated component DNN units: ITNet and DualNet. This leads to a novel collaborative feature learning policy where individual BSs can identify their beam features by exchanging scalar coordination messages. The ITNet generates the IT constraint values which are shared among BSs by using the local CSI only. Also, the DualNet is responsible for inferring the optimal dual variables based on the IT constraint messages obtained from other BSs. The resulting dual variables act as final beam features. By doing so, each BS can determine its beamforming solution in a decentralized manner with limited information sharing. Notably, component DNN units can be reused at all BSs since the computation processes of the optimized IT constraints and the dual variables are identical for all BSs. Thus, a sole set of component DNNs is sufficient to produce the beamforming vectors of the entire MISO IC networks. As a result, the proposed feature learning can achieve the decentralization of beamforming optimization as well as the scalability with respect to the number of the BSs.

Conventional joint training strategies of the ITNet and DualNet fail to learn valid beam features since it cannot inject the optimal behavior of each beam feature. To address this challenge, we propose an alternative training strategy which train ITNet and DualNet with distinct training objective functions. This algorithm is inspired by the primal-dual method [34] which optimizes primal and dual variables in an alternating manner. The IT constraints computed by the ITNet become the primal variable that identifies the beamforming vector. Thus, it is trained to maximize the desired network utility performance. On the contrary, the training of the DualNet is supervised by the dual function evaluated by the IT constraints. It is optimized to solve the dual problem of the decentralized beamforming optimization. The proposed alternating training algorithm can also be decentralized using backhaul coordination among BSs. The viability of the proposed decentralized learning-based beamforming framework is demonstrated through numerical simulations.

The remainder of this paper is organized as follows: Section II introduces a system model for MISO IC networks and formulates a Pareto boundary characterization task of an achievable rate region. A novel beamforming optimization DL structure is proposed in Section III, and its training strategy is provided in Section IV. In Section V, we present numerical simulations to assess the proposed framework. The paper is terminated with concluding remarks in Section VI.

Notation: We employ uppercase boldface letters, lowercase boldface letters, and normal letters for matrices, column vectors, and scalar quantities, respectively. Also, $\mathbb{E}_X[\cdot]$ represents an expectation operator over a random variable X. The sets of complex and real vectors of length m are denoted by $\mathbb{C}^m$ and $\mathbb{R}^m$, respectively, and $\mathbb{C}^{m\times n}$ indicates the set of m-by-n complex matrices. All-zero column vector is written by $\mathbf{0}$ and an identity matrix is expressed by $\mathbf{I}$.

II. SYSTEM MODEL

Consider a MISO IC where each of K BSs with M_T antennas serves their own single-antenna receiver. Let $\mathbf{w}_k \in \mathbb{C}^{M_T}$ be the beamforming vector at BS k ($k = 1, \ldots, K$). The power constraint for BS k is imposed as $\|\mathbf{w}_k\| \leq P$ where P is the transmit power budget. Denoting $\mathbf{h}_{kj} \in \mathbb{C}^{M_T}$ as the channel vector from BS k to receiver j. By using standard channel acquisition processes [4], BS k can attain its local CSI vector $\mathbf{h}_k$ which collects the channel vectors between all users. It is defined as

$$\mathbf{h}_k \triangleq \{\mathbf{h}_{kj} : \forall j\}. \tag{1}$$

The achievable rate $R_k(\mathbf{H}, \mathbf{W})$ of receiver k is given by

$$R_k(\mathbf{H}, \mathbf{W}) = \log_2\left(1 + \frac{|\mathbf{h}_{kk}^H \mathbf{w}_k|^2}{\sum_{j\neq k} |\mathbf{h}_{jk}^H \mathbf{w}_j|^2 + \sigma^2}\right), \tag{2}$$

where $\mathbf{H} \triangleq \{\mathbf{h}_k : \forall k\} \in \mathbb{C}^{M_T K\times K}$ stands for the global CSI matrix, $\mathbf{W} \triangleq \{\mathbf{w}_k : \forall k\} \in \mathbb{C}^{M_T\times K}$ indicates the beamforming matrix, and σ^2 is the noise variance.

In the MISO IC, mutual interference incurs a nontrivial tradeoff among achievable rates. Such an issue can be formalized as the identification of the Pareto boundary of the achievable rate region, which is defined as a set of rate tuples $\mathbf{R}(\mathbf{H}, \mathbf{W}) \triangleq (R_1(\mathbf{H}, \mathbf{W}), \cdots, R_K(\mathbf{H}, \mathbf{W}))$ over all feasible beamforming vectors $\|\mathbf{w}_k\|^2 \leq P, \forall k$. The rate tuple $\mathbf{R}(\mathbf{H}, \mathbf{W})$ is referred to as the Pareto optimal point if there is no other rate tuple $\mathbf{R}(\mathbf{H}, \mathbf{W}')$ with $\mathbf{W}'$ such that $R_k(\mathbf{H}, \mathbf{W}') \geq R_k(\mathbf{H}, \mathbf{W}), \forall k$. Therefore, at the Pareto boundary point, rates cannot be improved without sacrificing others. A set of the Pareto optimal points collectively form the Pareto boundary containing upper-right boundary points of the rate region.

We aim to determine the Pareto boundary of the achievable rate region. This invokes a multi-objective optimization (MOO) task which maximizes a group of achievable rates $\mathbf{R}(\mathbf{H}, \mathbf{W})$ simultaneously. This can be formulated as

$$\max_{\mathbf{W}\in\mathcal{W}} \mathbf{R}(\mathbf{H}, \mathbf{W}) \tag{3}$$

where $\mathcal{W} \triangleq \{\mathbf{W} : \|\mathbf{w}_k\|^2 \leq P, \forall k\}$ indicates the feasible set of beamforming vectors. The MOO problem (3) requires tackling the vector-valued objective function $\mathbf{R}(\mathbf{H}, \mathbf{W})$, which is nontrivial for existing scalar objective optimization algorithms. To address this difficulty, various parameterization techniques were proposed which transform the vector-valued objective into equivalent single objective optimization tasks. In what follows, we discuss conventional approaches to solve (3).

A. SCALARIZATION METHODS

The scalarization approaches [35] reformulate the MOO task (3) by employing a scalar utility function $u(\cdot)$. Defining $\boldsymbol{\mu} \triangleq \{\mu_k : \forall k\}$ with non-negative weights $\mu_k \geq 0, \forall k$, an equivalent single objective optimization task of (3) can be formulated as

$$\max_{\mathbf{W}\in\mathcal{W}} u(\mathbf{R}(\mathbf{H}, \mathbf{W}), \boldsymbol{\mu}). \tag{4}$$

Popular candidates of $u(\cdot)$ include the WSR $u_{\text{WSR}}(\cdot)$ and WMR $u_{\text{WMR}}(\cdot)$, which are respectively defined as

$$u_{\text{WSR}}(\mathbf{R}(\mathbf{H}, \mathbf{W}), \boldsymbol{\mu}) = \sum_{k=1}^{K} \mu_k R_k(\mathbf{H}, \mathbf{W}), \tag{5}$$

$$u_{\text{WMR}}(\mathbf{R}(\mathbf{H}, \mathbf{W}), \boldsymbol{\mu}) = \min_k \mu_k R_k(\mathbf{H}, \mathbf{W}). \tag{6}$$

In both utility functions, the weight μ_k can be interpreted as the QoS requirement of receiver k. Receiver k can increase μ_k to request a higher rate $R_k(\mathbf{H}, \mathbf{W})$ as its contribution to the utility function grows. On the contrary, low-rate receivers decrease their weights so that interference toward other receivers can be reduced. Therefore, the beamforming vectors achieving an arbitrary rate tradeoff $\mathbf{R}(\mathbf{H}, \mathbf{W})$ would be identified by controlling the weight vector $\boldsymbol{\mu}$. It has been revealed that the WSR utility fails to characterize the Pareto boundary points for nonconvex rate regions [15], whereas the WMR utility guarantees the complete characterization of all Pareto optimal points [35].

Solving (3) invokes centralized calculations by collecting the global CSI $\mathbf{H}$ at a central computing unit [36], [37], [38]. Such a centralized beamforming optimization process is, however, impractical due to high system complexity. Thus, decentralized signal processing is desirable where each BS decides its own beamforming vector based only on local CSI and coordination messages obtained from other BSs.

B. PARAMETERIZATION USING INTERFERENCE TEMPERATURE

A decentralized beamforming method [6] parameterizes the Pareto optimal beamforming vector $\mathbf{w}_k$ by using IT vectors $\hat{\mathbf{c}}_k \triangleq \{c_{kj} : \forall j \neq k\} \in \mathbb{R}^{K-1}$ and $\check{\mathbf{c}}_k \triangleq \{c_{jk} : \forall j \neq k\} \in \mathbb{R}^{K-1}$. These parameters control signal powers of interfering links and interfered links of BS k, respectively. They decompose the centralized optimization problem (3) into K subproblems each dedicated to the beamforming optimization for BS k. The corresponding subproblem is written as

$$r_k(\mathbf{h}_k, \check{\mathbf{c}}_k, \hat{\mathbf{c}}_k) = \max_{\mathbf{w}_k} \log_2\left(1 + \frac{|\mathbf{h}_{kk}^H \mathbf{w}_k|^2}{\sum_{j\neq k} c_{jk} + \sigma^2}\right) \tag{7a}$$

$$\text{subject to } |\mathbf{h}_{kj}^H \mathbf{w}_k|^2 \leq c_{kj}, \forall j \neq k \tag{7b}$$

$$\|\mathbf{w}_k\|^2 \leq P, \tag{7c}$$

where the IT constraint (7b) restricts the interfering signal power to unintended receiver j. The optimal value of problem (7) $r_k(\mathbf{h}_k, \check{\mathbf{c}}_k, \hat{\mathbf{c}}_k)$ indicates the achievable rate of receiver k for given IT constraints $\hat{\mathbf{c}}_k$ and $\check{\mathbf{c}}_k$. A particular Pareto boundary point can be attained by solving K subproblems in parallel across the BSs by fixing $\{c_{kj} : \forall j, k\}$.

Unlike the scalarization technique in (4) which can proactively control the rate tradeoff among the receivers using their QoS requirements $\boldsymbol{\mu}$, this parameterization fails to incorporate such receiver-centric features. Consequently, the resulting beamforming vectors lead to undesired rate performance, and thus it cannot characterize the complete Pareto boundary. Therefore, (7) should employ numerous initializations of $\check{\mathbf{c}}_k$ and $\hat{\mathbf{c}}_k$ which requests intensive computations.

III. DECENTRALIZED BEAMFORMING INFERENCE

To address the aforementioned challenges, we propose a novel DL-based beamforming optimization framework which consolidates the advantages of both the scalarization method and the decentralized method in [6]. Our design goal is to build a proper DNN model $\mathcal{V}_\theta(\cdot)$ with a trainable parameter θ that maps a tuple $(\mathbf{H}, \boldsymbol{\mu})$ to the beamforming matrix $\mathbf{W}$ as

$$\mathbf{W} = \mathcal{V}_\theta(\mathbf{H}, \boldsymbol{\mu}). \tag{8}$$

The DBL approach employs several fully-connected layers $\mathcal{V}_\theta(\cdot)$ with the output activation $\Pi_{\mathcal{W}_k}(\mathbf{w}_k) = \min_{\mathbf{x}\in\mathcal{W}_k} \|\mathbf{w}_k - \mathbf{x}\|^2$ that forces the beamforming vector $\mathbf{w}_k$ to lie in the feasible set $\mathcal{W}_k$. The DNN $\mathcal{V}_\theta(\cdot)$ requires a central process by means of centrally collected global CSI $\mathbf{H}$ and the weight vector $\boldsymbol{\mu}$. For this reason, the central processing unit is required to execute both the training and inference steps. Also, the DNN model has fixed input and output dimensions, thereby lacking the adaptability to networks with arbitrary numbers of BSs K. Furthermore, it has been reported from [21], [24], and [28] that the DBL fails to learn the effective beamforming solution from the input channel matrix $\mathbf{H}$.

A. PROPOSED FEATURE LEARNING ARCHITECTURE

To address these difficulties, we propose a novel feature learning policy which exploits the expert knowledge of the decentralized beamforming formalism (7) in constructing the DNN $\mathcal{V}_\theta(\cdot)$. To this end, we first analyze the optimal solution to (7). Let $d_{kj} \geq 0$ and $d_{kk} \geq 0$, $\forall j \neq k$, respectively denote dual variables associated with (7b) and (7c). For given local CSI $\mathbf{h}_k$ and IT constraints $\check{\mathbf{c}}_k$ and $\hat{\mathbf{c}}_k$, the Lagrangian is expressed as

$$\begin{aligned} &L(\mathbf{w}_k, \mathbf{d}_k; \mathbf{h}_k, \check{\mathbf{c}}_k, \hat{\mathbf{c}}_k) \\ &\quad= \log_2\left(1 + \frac{|\mathbf{h}_{kk}^H \mathbf{w}_k|^2}{\sum_{j\neq k} c_{jk} + \sigma^2}\right) \\ &\qquad - \sum_{j\neq k} d_{kj}\left(|\mathbf{h}_{kj}^H \mathbf{w}_k|^2 - c_{kj}\right) - d_{kk}\left(\|\mathbf{w}_k\|^2 - P\right), \end{aligned} \tag{9}$$

where $\mathbf{d}_k \triangleq \{d_{kj} : \forall j\} \in \mathbb{R}^K$. The dual function is given by

$$g(\mathbf{d}_k; \mathbf{h}_k, \check{\mathbf{c}}_k, \hat{\mathbf{c}}_k) = \max_{\mathbf{w}_k} L(\mathbf{w}_k, \mathbf{d}_k; \mathbf{h}_k, \check{\mathbf{c}}_k, \hat{\mathbf{c}}_k), \tag{10}$$

and its optimal solution can be calculated as

$$\mathbf{w}_k = V(\mathbf{h}_k, \check{\mathbf{c}}_k, \mathbf{d}_k) \triangleq \sqrt{p_k}\mathbf{A}_k^{-1}\mathbf{h}_{kk}, \tag{11}$$

where $V(\cdot)$ indicates the beam recovery function, and $\mathbf{A}_k$ and the power control value p_k are respectively defined as

$$\mathbf{A}_k \triangleq \sum_{j\neq k} d_{kj}\mathbf{h}_{kj}\mathbf{h}_{kj}^H + d_{kk}\mathbf{I}, \tag{12a}$$

$$p_k \triangleq \left(\frac{1}{\ln 2} - \frac{\sum_{j\neq k} c_{jk} + \sigma^2}{\|\mathbf{A}_k^{-\frac{1}{2}}\mathbf{h}_{kk}\|^2}\right)^+ \frac{1}{\|\mathbf{A}_k^{-\frac{1}{2}}\mathbf{h}_{kk}\|^2} \tag{12b}$$

with $(x)^+ \triangleq \max(0, x)$. Also, the optimal dual variable $\boldsymbol{d}_k$ can be obtained by solving the dual problem formulated as

$$\min_{\mathbf{d}_k \geq 0} g(\mathbf{d}_k; \mathbf{h}_k, \check{\mathbf{c}}_k, \hat{\mathbf{c}}_k). \tag{13}$$

The optimal beam structure (11) indicates that the beam features of $\mathbf{w}_k$ include the IT constraint $\check{\mathbf{c}}_k$ on the interfered links and the dual variable $\mathbf{d}_k$. Also, we can see from (13) that $\hat{\mathbf{c}}_k$ on the interfering links plays a key role in identifying the optimal dual variable. Therefore, these three features are regarded as sufficient statistics to recover the optimal beamforming vector $\mathbf{w}_k$. As a consequence, the proposed feature learning policy aims at computing $3K-2$ real variables, which are much smaller than the number of optimization variables of the DBL given by $2M_TK$. Such a reduction in the optimization dimension leads to a lightweight DNN with improved training performance.

The remaining work is to construct a valid beam feature DNN $\mathcal{F}_{\theta_k}(\cdot)$ with a trainable parameter θ_k that is responsible for yielding the efficient beam feature vector $(\hat{\mathbf{c}}_k, \check{\mathbf{c}}_k, \mathbf{d}_k)$. With a properly trained DNN $\mathcal{F}_{\theta_k}(\cdot)$ at hands, BS k can readily retrieve its beamforming vector $\mathbf{w}_k$ using the beam recovery operator $V(\cdot)$ in (11). In the following, we present several important properties of the efficient DNN $\mathcal{F}_{\theta_k}(\cdot)$ based on the underlying principles of optimization procedures (9)-(13).

- *Decentralized Computation:* The Lagrangian in (9) can be calculated only with the local CSI $\mathbf{h}_k$ and IT constraints $\check{\mathbf{c}}_k$ and $\hat{\mathbf{c}}_k$. This implies that these locally observable vectors are sufficient to infer the optimal dual variable $\mathbf{d}_k$ in (13). This results in the decentralized learning structure where BSs calculate their beam features individually using local information only.
- *Parameter Sharing:* It is important to note that computation processes of the Lagrangian $L(\cdot)$, dual function $g(\cdot)$, and beam recovery operator $V(\cdot)$ are identical for all BSs. Utilizing this property, we adopt the parameter sharing technique where all BSs reuse the identical DNN model $\mathcal{F}_{\theta}(\cdot)$ to obtain their beam features. This brings up a versatile computational architecture where a sole DNN $\mathcal{F}_{\theta}(\cdot)$ determines the beam features of all BSs.
- *Cooperative Inference:* The IT constraint c_{jk} in (7b) is associated with the interfered channel $\mathbf{h}_{jk}$, which is unavailable at BS k. Hence, its optimal value cannot be directly inferred by BS k. This triggers the development of a cooperative learning policy where BS j computes its IT constraint c_{jk} and forwards it to BS k. BS k is responsible for identifying its interfering IT constraint $\hat{\mathbf{c}}_k$, whereas the interfered IT constraint $\check{\mathbf{c}}_k$ can be collected from other BSs through backhaul coordination. Therefore, the beam feature DNN $\mathcal{F}_{\theta}(\cdot)$ leverages $\hat{\mathbf{c}}_k$ and $\check{\mathbf{c}}_k$ as output and input, respectively.
- *Manageability:* The major drawback of the IT constraint formulation (7) is that the BSs cannot incorporate the QoS requests from the receivers into the beamforming optimization. Thus, it loses the manageability that achieves a desired Pareto optimal rate tuple. To this end, we adopt the weight μ_k as the side information to the DNN $\mathcal{F}_{\theta}(\cdot)$ so that the resulting beam features become controllable with the input weight.

Based on the above intuitions, the proposed DNN $\mathcal{F}_{\theta}(\cdot)$ can be written by

$$(\hat{\mathbf{c}}_k, \mathbf{d}_k) = \mathcal{F}_{\theta}(\mathbf{h}_k, \mu_k, \check{\mathbf{c}}_k). \tag{14}$$

B. INFERENCE STRUCTURE

The Lagrange duality analysis in (13) reveals that we need to determine the IT constraint $\hat{\mathbf{c}}_k$ before the optimization process of the dual variable $\mathbf{d}_k$ which maximizes the dual function $g(\mathbf{d}_k; \mathbf{h}_k, \check{\mathbf{c}}_k, \hat{\mathbf{c}}_k)$. Inspired by this property, we split the proposed beam feature DNN $\mathcal{F}_{\theta}(\cdot)$ into two component DNNs, namely ITNet $\mathcal{C}_{\theta_C}(\cdot)$ and DualNet $\mathcal{D}_{\theta_D}(\cdot)$, each with trainable parameters θ_C and θ_D, respectively. Such a DNN decomposition approach leads to a decentralized and cooperative learning architecture where individual BSs identify their beamforming vectors separately by means of DNN-assisted backhaul coordination strategies. The ITNet $\mathcal{C}_{\theta_C}(\cdot)$ is responsible for the coordination among BSs by creating the IT constraint c_{kj}, $\forall j \neq k$, at BS k. Subsequently, the DualNet $\mathcal{D}_{\theta_D}(\cdot)$ infers the optimized dual variable $\mathbf{d}_k$ based on the IT constraint values sent by other BSs. As illustrated in Figure 1, a group of the ITNets and DualNets establishes the beam feature DNN $\mathcal{F}_{\theta}(\cdot)$ with $\theta = \{\theta_C, \theta_D\}$. These component DNNs form three inference steps: IT constraint generation, dual variable generation, and beam recovery. The details of each step are described in the following.

1) IT CONSTRAINT GENERATION

BS k first creates its IT values c_{kj}, by using the ITNet $\mathcal{C}_{\theta_C}(\cdot)$. Recall that c_{kj} in (7b) regulates the interference power $|\mathbf{h}_{kj}^H \mathbf{w}_k|^2$ originated from BS k to BS j. Thus, to determine a proper c_{kj}, it is necessary to exploit the channel vector $\mathbf{h}_{kj}$ as an input to $\mathcal{C}_{\theta_C}(\cdot)$. Since the main purpose of $\mathbf{w}_k$ is to improve the desired link quality $|\mathbf{h}_{kk}^H \mathbf{w}_k|^2$, c_{kj} also depends on $\mathbf{h}_{kk}$ as well as the corresponding QoS requirement μ_k. Based on these intuitions, an input-output relationship of the ITNet is designed as

$$c_{kj} = \mathcal{C}_{\theta_C}(\mathbf{h}_{kk}, \mathbf{h}_{kj}, \mu_k). \tag{15}$$

Note that the input and output dimensions of the ITNet are irrelevant to the network size K. This leads to a scalable calculation architecture with respect to arbitrary K. Since c_{kj} acts as an upper bound for the interfering signal power $|\mathbf{h}_{kj}^H \mathbf{w}_k|^2$, it is bounded by $c_{kj} \in [0, P\|\mathbf{h}_{kj}\|^2]$. Such a constraint can be simply imposed by employing the sigmoid function at the output layer. The resulting output is then multiplied by $P\|\mathbf{h}_{kj}\|^2$ to ensure the feasibility of c_{kj}.

The resulting IT constraint c_{kj} is leveraged as a scalar coordination message conveyed from BS k to its interfering BS j, $\forall j \neq k$. $K-1$ parallel processing of (15) results in the message vector $\hat{\mathbf{c}}_k$ as

$$\hat{\mathbf{c}}_k = \{\mathcal{C}_{\theta_C}(\mathbf{h}_{kk}, \mathbf{h}_{kj}, \mu_k) : \forall j \neq k\}. \tag{16}$$

This backhaul coordination message is further utilized in the subsequent dual variable generation step.

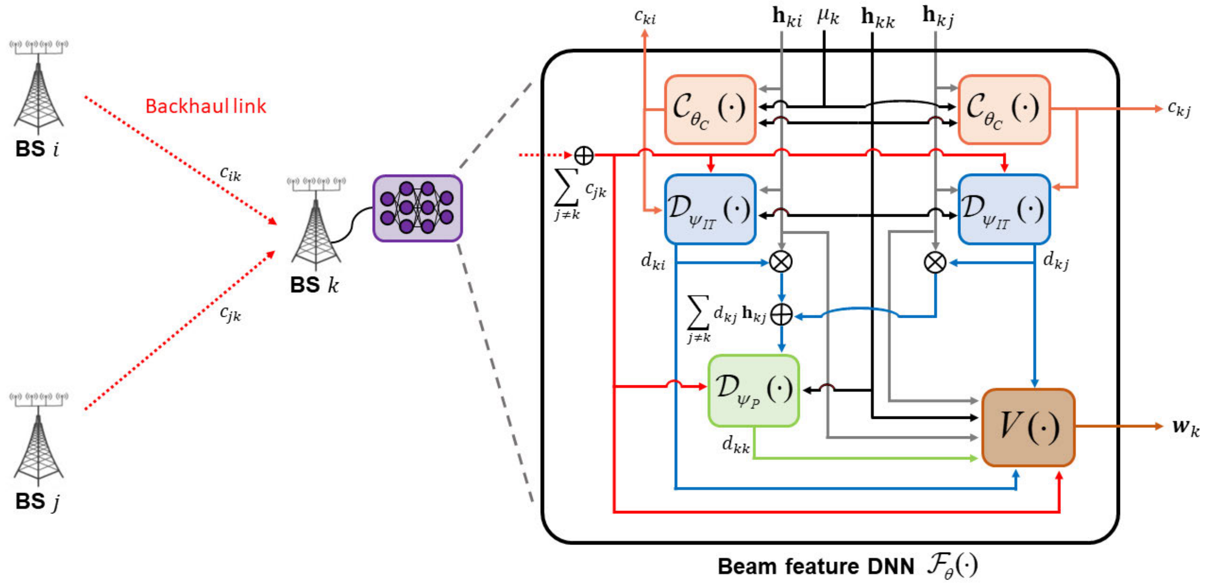


FIGURE 1. Proposed decentralized beamforming inference structure.

2) DUAL VARIABLE GENERATION

Receiving a set of incoming messages $\check{\mathbf{c}}_k$ leverages the DualNet $\mathcal{D}_{\theta_D}(\cdot)$ to create $\mathbf{d}_k$ in the dual variable generation step. As we can see from (9), $\mathbf{d}_k$ consists of two types of dual variables. More precisely, $\{d_{kj} : \forall j \neq k\}$ are associated with the IT constraints in (7b) for interfering BSs, while d_{kk} is intended to adjust the power constraint of BS k (7c). Such heterogeneous roles of the dual variables entail different computation procedures. To this end, the DualNet $\mathcal{D}_{\theta_D}(\cdot)$ is split to two subsequential DNN units $\mathcal{D}_{\psi_{IT}}(\cdot)$ and $\mathcal{D}_{\psi_P}(\cdot)$. Their trainable parameters ψ_{IT} and ψ_P collectively form $\theta_D = \{\psi_{IT}, \psi_P\}$, and these DNN modules determine the dual variables $\{d_{kj} : \forall j \neq k\}$ and d_{kk}, respectively.

We first focus on $\mathcal{D}_{\psi_{IT}}(\cdot)$ that produces d_{kj} associated with the IT constraint. According to the Lagrange duality analysis (13), the optimal dual variable minimizes the dual function $g(\cdot)$. To this end, d_{kj} can be optimized iteratively according to the subgradient of the Lagrangian calculated as

$$\begin{aligned}\partial_{d_{kj}} L(\mathbf{w}_k, \mathbf{d}_k; \mathbf{h}_k, \check{\mathbf{c}}_k, \hat{\mathbf{c}}_k)|_{\mathbf{w}_k = V(\mathbf{h}_k, \check{\mathbf{c}}_k, \mathbf{d}_k)} \\ = c_{kj} - |\mathbf{h}_{kj}^H V(\mathbf{h}_k, \check{\mathbf{c}}_k, \mathbf{d}_k)|^2. \end{aligned} \tag{17}$$

It can be checked from (17) that to get the optimal dual variable, we should exploit the IT constraint c_{kj}, interfering channel $\mathbf{h}_{kj}$, and the beamforming $\mathbf{w}_k = V(\mathbf{h}_k, \check{\mathbf{c}}_k, \mathbf{d}_k)$ obtained from the beam recovery process (11). Therefore, the inputs to $\mathcal{D}_{\varphi_{IT}}(\cdot)$ consist of the desired channel $\mathbf{h}_{kk}$ and the aggregated incoming message $\sum_{j\neq k} c_{jk}$, i.e., the total interference power, which are needed to calculate (12). Consequently, the DNN module $\mathcal{D}_{\psi_{IT}} : \mathbb{C}^{M_T} \times \mathbb{C}^{M_T} \times \mathbb{R} \times \mathbb{R} \rightarrow \mathbb{R}$ is designed as

$$d_{kj} = \mathcal{D}_{\psi_{IT}}\left(\mathbf{h}_{kk}, \mathbf{h}_{kj}, c_{kj}, \sum_{j\neq k} c_{jk}\right). \tag{18}$$

Next, we consider $\mathcal{D}_{\psi_P}(\cdot)$ that decides the dual variable d_{kk}. Note that d_{kk} regulates the transmit power of BS k, i.e., $\|\mathbf{w}_k\|^2$, by adjusting the power control variable p_k in (12b). Thus, valid inputs to $\mathcal{D}_{\psi_{IT}}(\cdot)$ should include $\mathbf{h}_{kk}$ and $\sum_{j\neq k} c_{jk}$. In addition, we adopt the weighted sum of interfering channels $\sum_{j\neq k} d_{kj}\mathbf{h}_{kj}$ required to extract latent features of $\mathbf{A}_k$ in (12a). According to these insights, the DNN $\mathcal{D}_{\psi_P} : \mathbb{C}^{M_T} \times \mathbb{C}^{M_T} \times \mathbb{R} \rightarrow \mathbb{R}$ is constructed as

$$d_{kk} = \mathcal{D}_{\psi_P}\left(\mathbf{h}_{kk}, \sum_{j\neq k} d_{kj}\mathbf{h}_{kj}, \sum_{j\neq k} c_{jk}\right). \tag{19}$$

The softplus activation function is employed at the output layer of $\mathcal{D}_{\psi_{IT}}(\cdot)$ and $\mathcal{D}_{\psi_P}(\cdot)$ to ensure the non-negative constraint on the dual variable. Finally, the DualNet $\mathcal{D}_{\theta_D}(\cdot)$ integrates $\mathcal{D}_{\psi_{IT}}(\cdot)$ in (18) and $\mathcal{D}_{\psi_P}(\cdot)$ in (19) into

$$\begin{aligned}\mathbf{d}_k &= \{d_{kj} : \forall j\} = \mathcal{D}_{\theta_D}(\mathbf{h}_k, \check{\mathbf{c}}_k, \hat{\mathbf{c}}_k) \\ &\triangleq \left\{\mathcal{D}_{\psi_{IT}}\left(\mathbf{h}_{kk}, \mathbf{h}_{kj}, c_{kj}, \sum_{j\neq k} c_{jk}\right) : \forall j \neq k\right\} \\ &\quad \bigcup \mathcal{D}_{\psi_P}\left(\mathbf{h}_{kk}, \sum_{j\neq k} d_{kj}\mathbf{h}_{kj}, \sum_{j\neq k} c_{jk}\right), \end{aligned} \tag{20}$$

where

$$\check{\mathbf{c}}_k = \{\mathcal{C}_{\theta_C}(\mathbf{h}_{jj}, \mathbf{h}_{jk}, \mu_j) : \forall j \neq k\}. \tag{21}$$

3) BEAM RECOVERY

With component DNNs $\mathcal{C}_{\theta_C}(\cdot)$ and $\mathcal{D}_{\theta_D}(\cdot)$ at hands, BS k can obtain its beam features $\hat{\mathbf{c}}_k$, $\check{\mathbf{c}}_k$ and $\mathbf{d}_k$ with the decentralized collaboration among other BSs. Therefore, the forward-pass calculation of the beam feature DNN $\mathcal{F}_\theta(\cdot)$ in (14) can be defined as a sequential computation of the ITNet (15) and

DualNet (20). Along with $\mathbf{h}_k$, the beam recovery function $V(\cdot)$ in (11) is applied to the output beam feature to successfully retrieve the optimized $\mathbf{w}_k$. These decentralized operations collectively form the final beamforming optimizer $\mathcal{V}_\theta(\cdot)$ in (8) as

$$\mathbf{W} = \{\mathbf{w}_k : \forall k\} = \mathcal{V}_\theta(\mathbf{H}, \boldsymbol{\mu}) \triangleq \{V(\mathbf{h}_k, \check{\mathbf{c}}_k, \mathbf{d}_k) : \forall k\}. \quad (22)$$

Algorithm 1 summarizes the forward-pass computation processes of the proposed DL-based decentralized beamforming strategy. In the IT constraint generation step, BS k, individually determines $\hat{\mathbf{c}}_k$ by carrying out the ITNet $\mathcal{C}_{\theta_C}(\cdot)$ $K-1$ times. BSs can facilitate parallel calculations to enhance the computational efficiency. These are forwarded to interfering BSs j, $\forall j \neq k$, through interconnected backhaul links. This backhaul coordination step invokes $K(K-1)$ channel uses to share the set of backhaul messages $\hat{\mathbf{c}}_k$ among all BSs k. As a result, the backhaul signaling overhead of the proposed method is much lower than that of the centralized beamforming methods that need $2M_T K^2$ channel uses to exchange all local CSI vectors. Notice that the backhaul coordination is needed at each coherence time block during which the channel vectors remain unchanged. After the backhaul coordination, in the dual variable generation step, BS k, employs the DualNet $\mathcal{D}_{\theta_D}(\cdot)$ to calculate the dual variable $\mathbf{d}_k$ in parallel. It is then followed by the decentralized beam recovery step where BS k obtains its beamforming vector $\mathbf{w}_k$ using $V(\cdot)$ in (11).

Algorithm 1 Proposed Decentralized Beamforming Inference

1) *IT constraint generation*
for $k = 1 : K$
  for $j \neq k$
    BS k calculates c_{kj} from (15).
    BS k sends c_{kj} to interfering BS j.
2) *Dual variable generation*
for $k = 1 : K$
  for $j \neq k$
    BS k calculates d_{kj} from (18).
  BS k calculates d_{kk} from (19).
3) *Beam recovery*
for $k = 1 : K$
  BS k calculates $\mathbf{w}_k$ from (11).

IV. PROPOSED TRAINING STRATEGY

This section presents a training mechanism of the proposed DL-based beamforming technique which optimizes the ITNet and DualNet. To identify the Pareto optimal boundary points, the training objective function $J(\theta)$ is chosen as the scalarization utility (4) expected over realizations of the global CSI $\mathbf{H}$ and the QoS requirement $\boldsymbol{\mu}$ as

$$J(\theta) = \mathbb{E}_{\mathcal{H},\mathcal{M}}\left[u(\mathbf{R}(\mathbf{H}, \mathcal{V}_\theta(\mathbf{H}, \boldsymbol{\mu})), \boldsymbol{\mu})\right], \quad (23)$$

where $\mathcal{V}_\theta(\cdot)$ is defined in (22) and $\mathcal{H} \triangleq \{\mathbf{H}\}$ and $\mathcal{M}$ indicate mini-batch datasets containing training samples of $\mathbf{H}$ and $\boldsymbol{\mu}$, respectively. The inclusion of the weight vector into $\mathcal{M}$ ensures the manageability of the trained DNN so that it can yield the Pareto optimal beamforming vectors achieving the desired rate tradeoff performance according to arbitrary QoS requirement $\boldsymbol{\mu}$. Consequently, by controlling the weight input $\boldsymbol{\mu}$ to the DNN $\mathcal{V}_\theta(\mathbf{H}, \boldsymbol{\mu})$, we can obtain multiple Pareto optimal boundary points simultaneously. The training process for maximizing $J(\theta)$ can be readily realized using stochastic gradient descent (SGD) methods. At the t-th epoch, the DNN parameter $\theta^{[t]}$ can be calculated as

$$\theta^{[t]} \leftarrow \theta^{[t-1]} + \eta \nabla_{\theta^{[t-1]}} J(\theta^{[t-1]}), \quad (24)$$

where ∇_Z stands for the gradient operator with respect to the variable Z and $\eta > 0$ indicates the learning rate.

The aforementioned training strategy updates the ITNet and DualNet jointly in an end-to-end manner. This conventional training mechanism has been adopted in existing beam feature learning methods [21], [22], [28]. However, the conventional training algorithm did not inject the underlying principles of the IT constraint and dual variable into the DNN $\mathcal{V}_\theta(\cdot)$. The feasibility of the IT constraint (7b) is regulated by the dual variable d_{kj}. To this end, the optimal dual variable should be a minimizer of the dual function, i.e., it is given by the optimal solution to the dual problem (13). The conventional training (24) cannot guarantee these important properties, since the ITNet and DualNet are simply trained to maximize the utility performance. For this reason, the learned beam features $\hat{\mathbf{c}}_k$, $\check{\mathbf{c}}_k$ and $\mathbf{d}_k$ would converge to unintended suboptimal points.

A. ALTERNATING TRAINING ALGORITHM

To handle such an issue, we propose a novel training algorithm that guides the ITNet and DualNet to learn the optimality conditions of the beam features. A key idea is to design dedicated training objective functions for each component DNN by exploiting the Lagrange duality analysis (9)-(13). By doing so, the optimal behaviors of the IT constraint and the dual variable are readily involved in the training phase. The ITNet needs to produce effective IT constraint values that determine the primal optimal beamforming vector $\mathbf{w}_k$ which maximizes the utility function $u(\cdot)$ in (4) measured by the optimal value of problem (7). In addition, the dual variable generated by the DualNet should be the solution to the dual problem (13). According to these intuitions, the training objective functions of the ITNet and DualNet are designed individually to achieve their dedicated goals. Such decomposed training objectives lead to an alternating training process that updates the ITNet and DualNet sequentially by fixing each other. The details of each update rule are given in the following.

1) ITNET UPDATE

We first discuss the ITNet update step which optimizes the ITNet $\mathcal{C}_{\theta_C}(\cdot)$ by fixing the DualNet $\mathcal{D}_{\theta_D}(\cdot)$. It is noted that

$J(\theta)$ in (23) leverages the rate $R_k(\mathbf{H}, \mathcal{V}_\theta(\mathbf{H}, \boldsymbol{\mu}))$ achieved by the end-to-end beamforming DNN $\mathbf{W} = \mathcal{V}_\theta(\mathbf{H}, \boldsymbol{\mu})$. Thus, the IT constraints $\check{\mathbf{c}}_k$ and $\hat{\mathbf{c}}_k$, can only be indirectly examined through the dual variable $\mathbf{d}_k$ obtained by the DualNet (20). This poses a challenge in calculating valid gradients with respect to the ITNet parameter θ_C. To this end, we develop a new training objective function dedicated to the ITNet so that it can characterize the relationship between the IT constraints and the system performance.

A key enabler is to exploit the objective function of (7) that has a closed-form mapping from the IT constraint to the achievable rate. At the t-th training epoch, the proposed training objective $J_C^{[t]}(\theta_C)$ of the ITNet is expressed as

$$J_C^{[t]}(\theta_C) = \mathbb{E}_{\mathcal{H},\mathcal{M}}\left[u(\{r_k^{[t-1]}(\mathbf{h}_k, \check{\mathbf{c}}_k, \hat{\mathbf{c}}_k) : \forall k\}, \boldsymbol{\mu})\right], \quad (25)$$

where $r_k^{[t]}(\mathbf{h}_k, \check{\mathbf{c}}_k, \hat{\mathbf{c}}_k)$ stands for the optimal value of problem (7) computed at the t-epoch as

$$r_k^{[t]}(\mathbf{h}_k, \check{\mathbf{c}}_k, \hat{\mathbf{c}}_k) = \log_2\left(1 + \frac{|\mathbf{h}_{kk}^H V(\mathbf{h}_k, \check{\mathbf{c}}_k^{[t-1]}, \mathbf{d}_k^{[t]})|^2}{\sum_{j\neq k} c_{jk}^{[t]} + \sigma^2}\right). \quad (26)$$

Here, the dual variable $\mathbf{d}_k^{[t]}$ at the t-th epoch is fixed as

$$\mathbf{d}_k^{[t]} = \mathcal{D}_{\theta_D^{[t]}}(\mathbf{h}_k, \check{\mathbf{c}}_k^{[t-1]}, \hat{\mathbf{c}}_k^{[t]}), \quad (27)$$

where $\check{\mathbf{c}}_k^{[t]} \triangleq \{c_{jk}^{[t]} : \forall j \neq k\}$ with $c_{kj}^{[t]}$ being the IT constraint as

$$c_{kj}^{[t]} = \mathcal{C}_{\theta_C^{[t]}}(\mathbf{h}_{kk}, \mathbf{h}_{kj}, \mu_k). \quad (28)$$

Unlike (23), the proposed objective function $J_C^{[t]}(\theta_C)$ in (25) can measure the impact of the IT constraints $\check{\mathbf{c}}_k$ and $\hat{\mathbf{c}}_k$ directly. By doing so, we can obtain a valid gradient for the ITNet parameter θ_C. At the t-th epoch, the SGD update rule for the ITNet becomes

$$\theta_C^{[t]} \leftarrow \theta_C^{[t-1]} + \eta_C \nabla_{\theta_C^{[t-1]}} J_C^{[t]}(\theta_C^{[t-1]}). \quad (29)$$

2) DUALNET UPDATE

The DualNet update step aims at minimizing the dual function $g(\mathbf{d}_k; \check{\mathbf{c}}_k, \hat{\mathbf{c}}_k)$. According to (10), the dual function can be calculated by using the Lagrangian $L(\mathbf{w}_k, \mathbf{d}_k; \check{\mathbf{c}}_k, \hat{\mathbf{c}}_k)$ with $\mathbf{w}_k = V(\mathbf{h}_{kk}, \check{\mathbf{c}}_k, \mathbf{d}_k)$ in (11). Thus, the dual function at the t-th epoch is written by

$$\begin{aligned} G^{[t]}(\mathbf{h}_k, \mathbf{d}_k) &\triangleq g(\mathbf{d}_k; \mathbf{h}_k, \check{\mathbf{c}}_k^{[t]}, \hat{\mathbf{c}}_k^{[t]}) \\ &= r_k^{[t-1]}(\mathbf{h}_k, \check{\mathbf{c}}_k, \hat{\mathbf{c}}_k) + q^{[t]}(\mathbf{h}_k, \mathbf{d}_k), \end{aligned} \quad (30)$$

where $q^{[t]}(\mathbf{h}_k, \mathbf{d}_k)$ is defined as

$$\begin{aligned} q^{[t]}(\mathbf{h}_k, \mathbf{d}_k) \triangleq &-\sum_{j\neq k} d_{kj}\left(|\mathbf{h}_{kj}^H V(\mathbf{h}_k, \check{\mathbf{c}}_k^{[t]}, \mathbf{d}_k^{[t-1]})|^2 - c_{kj}^{[t]}\right) \\ &- d_{kk}\left(\|V(\mathbf{h}_k, \check{\mathbf{c}}_k^{[t]}, \mathbf{d}_k^{[t-1]})\|^2 - P\right). \end{aligned} \quad (31)$$

As the first term in (30) is a constant with respect to the DualNet parameter θ_D, the training loss function of the DualNet $J_D^{[t]}(\theta_D)$ can be established as

$$\begin{aligned} J_D^{[t]}(\theta_D) &= \frac{1}{K}\sum_{k=1}^{K} \mathbb{E}_{\mathcal{H}_k,\mathcal{M}_k}\left[q^{[t]}(\mathbf{h}_k, \mathbf{d}_k)\right] \\ &\triangleq \frac{1}{K}\sum_{k=1}^{K} Q_k^{[t]}(\theta_D), \end{aligned} \quad (32)$$

where $\mathcal{H}_k$ and $\mathcal{M}_k$ stand for the dataset containing the local CSI $\mathbf{h}_k$ and weight μ_k, respectively, and $Q_k^{[t]}(\theta_D) \triangleq \mathbb{E}_{\mathcal{H}_k,\mathcal{M}_k}\left[q^{[t]}(\mathbf{h}_k, \mathbf{d}_k)\right]$ represents the average dual function of BS k. As a consequence, the DualNet update strategy to minimize $J_D^{[t]}(\theta_D)$ is obtained as

$$\theta_D^{[t]} \leftarrow \theta_D^{[t-1]} - \eta_D \nabla_{\theta_D^{[t-1]}} J_D^{[t]}(\theta_D^{[t-1]}) \quad (33)$$

with $\eta_D > 0$ being the learning rate.

Algorithm 2 Proposed Alternating Training Algorithm

```
Initialize θ_C^[0] and θ_D^[0].
for epoch t = 1, 2, ..., T_max
    1) Dataset preparation
    for k = 1 : K
        BS k samples H_k and M_k.
    2) ITNet update
    for k = 1 : K
        BS calculates d_k^[t-1] from (27).
    BSs update θ_C^[t] from (29).
    3) DualNet update
    for k = 1 : K
        for j ≠ k
            BS k calculates c_kj^[t] from (28).
            BS k sends c_kj^[t] to BS j.
    BSs update θ_D^[t] from (33).
```

The proposed training policy is summarized in Algorithm 2 which adjusts the DNN parameters θ_C and θ_D in an alternating manner. At the beginning of each training epoch, BS k randomly samples its local mini-batch sets $\mathcal{H}_k = \{\mathbf{h}_k\}$ and $\mathcal{M}_k = \{\mu_k\}$. The local CSI is generated using the Rayleigh fading model, whereas the weights are evenly distributed over the bounded range $\mu_k \in [0, 1]$. Then, BS k individually computes the dual variable $\mathbf{d}_k^{[t-1]}$ by leveraging the previous DualNet parameter $\theta_D^{[t-1]}$. Similar to Algorithm 1, this forward-pass procedure can be realized in parallel across individual BSs. It is then followed by the ITNet update in (29) to maximize the training objective function $J_C^{[t]}(\theta_C)$ in (25) evaluated over the global mini-batch $\mathcal{H}$ and $\mathcal{M}$. Next, the IT constraint $\check{\mathbf{c}}_k^{[t]}$ is derived from (28) along with the backhaul coordination presented in Algorithm 1. Finally, we can carry out the DualNet update in (33). These processes are repeated until the maximum number of epochs $T_{\max}$. After the training is performed in the offline domain, trained DNNs are installed at the BSs for the decentralized decision of the beamforming vectors.

Unlike the conventional joint training algorithm (24) which backpropagates gradients from the DualNet to the ITNet, in the proposed alternating process, these component DNNs interplay with each other by means of the training objective functions $J_C^{[t]}(\theta_C)$ and $J_D^{[t]}(\theta_D)$ evaluated from the optimized IT constraints and dual variables. The DualNet controls the feasibility of the beamforming vector $\mathbf{w}_k$ by solving the dual problem (13). The resulting dual variables help the ITNet obey the maximum allowable interference power threshold (7b). It is further optimized to improve the optimal value of problem (7) for given dual variables. This alternating procedure leads to the converged point with the zero duality gap. This will be proved in Section V via numerical results.

B. DECENTRALIZED IMPLEMENTATION

Now we discuss the decentralized implementation strategy of Algorithm 2 in which individual BSs execute the SGD updates in (29) and (33) in parallel. To this end, it is essential to develop a proper backhaul coordination protocol to allow BSs to share local information vectors relevant to the decentralized training. Notice that most parts of the proposed training algorithm can be readily realized in a decentralized manner except for the SGD update steps, i.e., lines 9 and 15 of Algorithm 2. More precisely, the gradient computations in (29) and (33) invoke centralized operations. With a careful investigation of the training objective functions, these SGD updates can be decoupled across the BSs by means the backhaul coordination.

We first focus on the ITNet update step (29). For simplicity, we remove the epoch index and arguments of the function $r_k^{[t]}(\mathbf{h}_k, \check{\mathbf{c}}_k, \hat{\mathbf{c}}_k)$. After some manipulations, the (sub)gradient vector $\nabla_{\theta_C} J_C(\theta_C)$ can be attained as

$$\nabla_{\theta_C} J_C(\theta_C) = \begin{cases} \mathbb{E}_{\mathcal{H},\mathcal{M}}\left[\sum_{k=1}^{K} \mu_k \nabla_{\theta_C} r_k\right] & \text{for } u_{\text{WSR}}(\cdot), \\ \mathbb{E}_{\mathcal{H},\mathcal{M}}\left[\min_k \mu_k \nabla_{\theta_C} r_k\right] & \text{for } u_{\text{WMR}}(\cdot), \end{cases} \tag{34}$$

where the gradient $\nabla_{\theta_C} r_k$ is derived as

$$\nabla_{\theta_C} r_k = \frac{\partial \hat{\mathbf{c}}_k}{\partial \theta_C} \nabla_{\hat{\mathbf{c}}_k} r_k + \sum_{j \neq k} \frac{\partial c_{jk}}{\partial \theta_C} \frac{\partial r_k}{\partial c_{jk}}. \tag{35}$$

The first term in (35) can be obtained locally by each BS via the backpropagation through the ITNet $\mathcal{C}_{\theta_C}(\cdot)$. Likewise, upon receiving c_{jk} from BS j, BS k can readily calculate the derivatives $\frac{\partial r_k}{\partial c_{jk}}$ in a closed-form expression as

$$\frac{\partial r_k}{\partial c_{jk}} = \frac{-|\mathbf{h}_{kk}^H V(\mathbf{h}_k, \check{\mathbf{c}}_k^{[t-1]}, \mathbf{d}_k^{[t]})|^2}{\ln 2 \left(1 + \frac{|\mathbf{h}_{kk}^H V(\mathbf{h}_k, \check{\mathbf{c}}_k^{[t-1]}, \mathbf{d}_k^{[t]})|^2}{\sum_{j \neq k} c_{jk}^{[t]} + \sigma^2}\right) \left(\sum_{j \neq k} c_{jk}^{[t]} + \sigma^2\right)^2}. \tag{36}$$

However, as this derivative cannot be acquired by BS k, this should be calculated at BS j and be forwarded to BS k. By collecting these derivatives, BS k successfully recovers the gradient vector $\nabla_{\theta_C} r_k$ of its achievable rate r_k. This vector is then multicast to all other BSs so that individual BSs can retrieve the entire gradient vector $\nabla_{\theta_C} J(\theta_C)$ in (34). With this at hands, each BS carries out the ITNet update policy (29) in a decentralized manner.

Next, to split the DualNet update step (33), we leverage the fact that BS k can determine its average dual function $Q_k(\theta_D)$ in (32) as well as its gradient $\nabla_{\theta_D} Q_k(\theta_D)$ by means of the local mini-batch sets $\mathcal{H}_k$ and $\mathcal{M}_k$. Then, BS k propagates $\nabla_{\theta_D} Q_k(\theta_D)$ to others in order to aggregate the gradient vector $\nabla_{\theta_D} J_D(\theta_D)$ as

$$\nabla_{\theta_D} J_D(\theta_D) = \frac{1}{K} \sum_{k=1}^{K} \nabla_{\theta_D} Q_k(\theta_D). \tag{37}$$

Finally, the BSs can proceed the DualNet update (33) individually.

The proposed decentralized training policy combines and enhances key operations of vertical and horizontal federated learning algorithms. In the ITNet update, the gradient exchanges (36) among BSs are inspired by the error backpropagation process of the vertical federated learning method [39]. However, the proposed algorithm differs from the vertical federated learning method in that we train a common model with partitioned data and further refine the gradient exchange process to minimize the overhead. Although the gradient aggregation (37) in the DualNet update step has been adopted in the horizontal federated learning [40], it can be performed individually without a central server. As a consequence, the BSs can successfully train the ITNet and DualNet in a decentralized manner by enhancing the federated learning algorithms.

C. SCALABILITY TO NETWORK SIZE AND LINK QUALITY

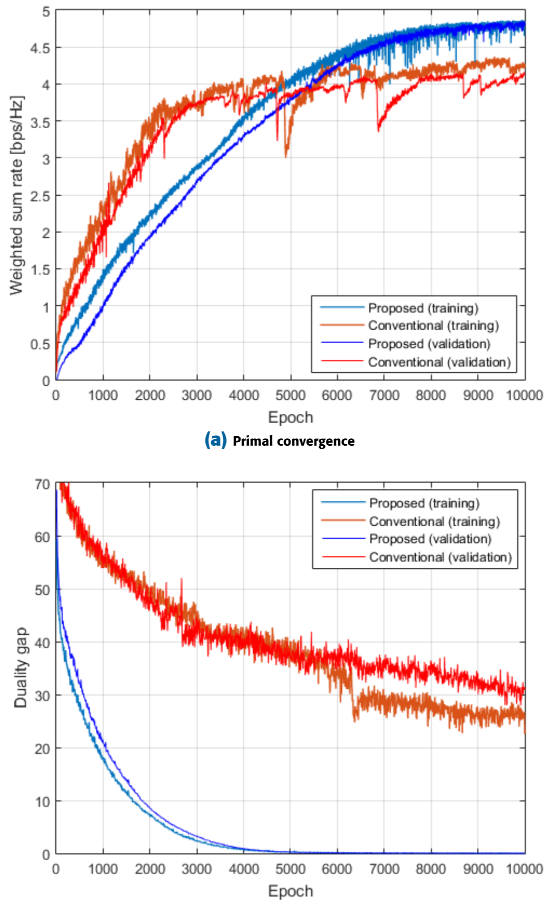
As discussed, the proposed framework has a versatile computation structure in terms of the number of BSs K since the identical ITNet and DualNet are shared at all BSs. To further improve the scalability to the network size, Algorithm 2 can be modified as follows: At each training epoch, we uniformly select K within a predefined range $[K_{\min}, K_{\max}]$ for each training data sample. Thanks to the parameter sharing policy, a sole set of $C_{\theta_C}(\cdot)$ and $D_{\theta_D}(\cdot)$ can handle these mini-batch samples with different K. The training computations can also be readily extended to an arbitrary K, since the training objective functions $J_C^{(t)}(\theta_C)$ and $J_D^{(t)}(\theta_D)$ are irrelevant to K. By doing so, the proposed DNN can be optimized over various BS populations, thereby enhancing the scalability.

Also, we can improve the adaptability of the proposed approach to varying link quality such as the pathloss. In our setup, this can be abstracted into the signal-to noise ratio (SNR) P/σ^2. Changes in the link quality request a new beamforming strategy for determining the power control variable p_k in (12b). As reported in [21] and [41], this issue can be tackled by taking the SNR as side information of the ITNet and DualNet. Thus, we involve P/σ^2 into the training dataset, and the trained DNN can be applied to any given SNR regime.

V. NUMERICAL RESULTS

This section validates the proposed DL-based decentralized beamforming framework through numerical results. To exploit standard real-valued DNNs, the channel vector input $\mathbf{h}_k \in \mathbb{C}^{M_T}$ is represented by an equivalent real-valued vector $[\Re\{\mathbf{h}_k\}^T, \Im\{\mathbf{h}_k\}^T]^T \in \mathbb{R}^{2M_T}$, where $\Re\{\cdot\}$ and $\Im\{\cdot\}$ respectively stand for real and imaginary parts. The Input dimensions of $\mathcal{C}_{\theta_C}(\cdot)$, $\mathcal{D}_{\psi_{IT}}(\cdot)$, $\mathcal{D}_{\psi_P}(\cdot)$ are respectively given by $4M_T + 1, 4M_T + 2$, and $4M_T + 1$. Both the ITNet and DualNet have four fully-connected hidden layers each with 800, 400, 100, and 30 neurons. The batch normalization technique is applied to each hidden layer along with the rectified linear unit (ReLU) activation. The Adam algorithm carries out the SGD updates (29) and (33) with the mini-batch size of 3×10^3 and the learning rates $\eta_C = 5 \times 10^{-4}$ and $\eta_D = 5 \times 10^{-3}$. The Rayleigh fading model is considered for the generation of training, validation, and test samples. The channel vectors for the desired links and interfering links are generated as $\mathbf{h}_{kk} \sim \mathcal{CN}(\mathbf{0}, \mathbf{I})$ and $\mathbf{h}_{kj} \sim \mathcal{CN}(\mathbf{0}, \alpha\mathbf{I})$, respectively, where $\alpha = 0.2$ indicates the average pathloss of the interfering links [42]. The proposed DNNs are trained over 10^5 epochs, resulting in total 3×10^8 training samples. The validation and test performance are evaluated over 3×10^3 independent channel realizations. Assuming the unit noise variance $\sigma^2 = 1$, the SNR is defined as P. To achieve the scalability, the proposed DNN is trained over $K \in [2, 4]$ and $P \in \{-5, 0, \cdots, 25\}$ dB.

Figure 2 shows the convergence of the proposed alternating training strategy in Algorithm 2 for $M_T = K = 2$. For comparison, we also plot the WSR performance of the conventional training algorithm (24) which updates the ITNet and DualNet simultaneously. Figure 2(a) exhibits the primal convergence by evaluating the training and validation WSR performance with respect to the training epochs. Both the proposed and conventional training strategies show almost identical training and validation performance, indicating that no over-fitting issues occur. The conventional approach improves the WSR performance fast, but eventually gets stuck to a suboptimal point after 4000 epochs. On the contrary, the performance of the proposed algorithm monotonically increases and outperforms the conventional training algorithm at the convergence. Such a performance gain can be explained from Figure 2(b) which depicts the convergence of the average duality gap calculated as $\mathbb{E}[g(\mathbf{d}_k; \mathbf{h}_k, \check{\mathbf{c}}_k, \hat{\mathbf{c}}_k) - L(\mathbf{w}_k, \mathbf{d}_k; \mathbf{h}_k, \check{\mathbf{c}}_k, \hat{\mathbf{c}}_k)]$. It can be checked that the proposed training algorithm achieves the zero duality gap after 4000 epochs, i.e., the strong duality holds at the output beamforming vector. This implies that the DualNet $\mathcal{D}_{\theta_D}(\cdot)$ produces a valid dual variable $\mathbf{d}_k$ that minimizes the dual function. On the contrary, a non-negative duality gap remains in the conventional method, meaning that it cannot learn the nature of the optimal dual variable. This results in the degraded WSR performance as observed from Figure 2(a). Therefore, we can conclude that the proposed alternating training method is more effective than conventional joint training strategies. This numerically shows the optimality of the proposed alternating training algorithm that achieves the zero duality gap.



(a) Primal convergence

(b) Dual convergence

FIGURE 2. Convergence behavior of various training algorithms for $M_T = K = 2$.

Next, we provide the achievable rate region of various beamforming techniques in Figure 3 for $M_T = K = 2$ and $P = 15$ dB. Cases 1 and 2 respectively correspond to scenarios where the rate regions are given by convex and nonconvex sets, respectively. The black solid line represents the optimal rate tradeoff curve generated by the Pareto optimal beamforming method [14], which requires exhaustive search to determine the beamforming vectors. In contrast, the proposed approach can find efficient beamforming solutions with simple linear matrix multiplications. The rate tuple achieved by the proposed framework with the WMR utility $u_{\text{WMR}}(\cdot)$ in (6) and the WMMSE method [9] as dots and plus sign markers, respectively. We consider two cases which correspond to convex and nonconvex rate regions in Figure 3. In both cases, the proposed method successfully identifies a

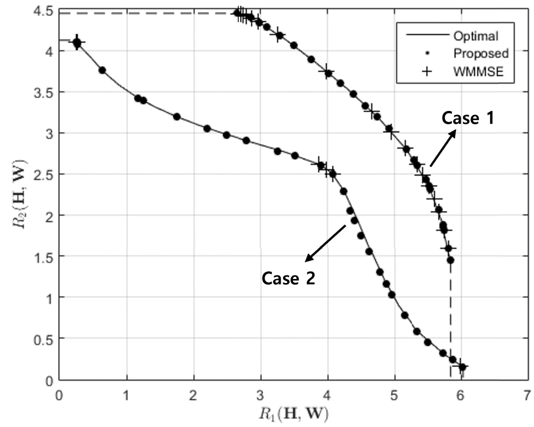
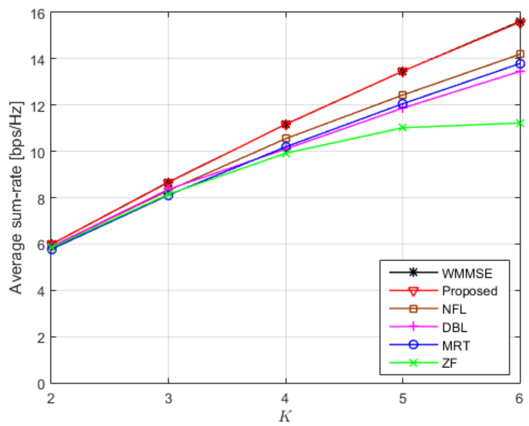
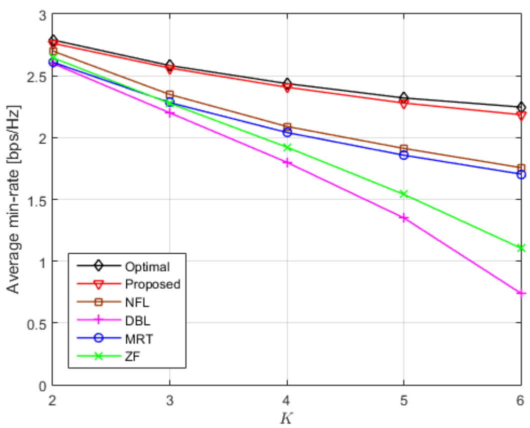


FIGURE 3. Achievable rate region for $M_T = K = 2$ and $P = 15$ dB.



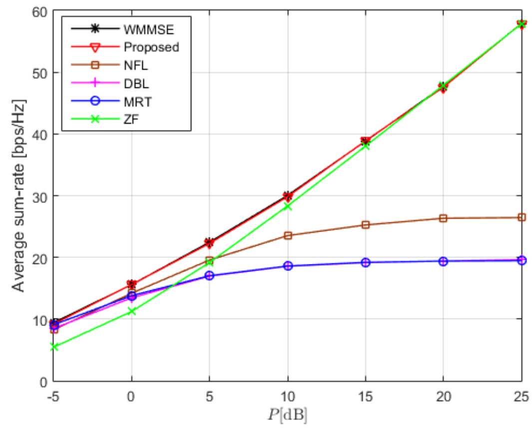
(a) Average sum-rate performance



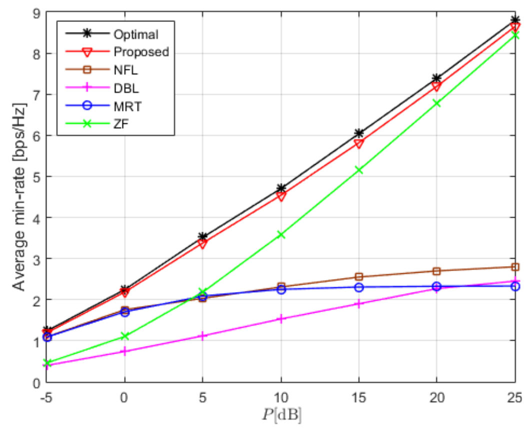
(b) Average min-rate performance

FIGURE 4. Sum-rate and min-rate performance with respect to K with $M_T = 8$ and $P = 0$ dB.

variety of boundary points on the Pareto-optimal rate region with little performance loss. However, the conventional WMMSE demonstrates limitations in encompassing the entire rate region, especially evident in nonconvex rate region scenarios. Under these conditions, it is observed that the rate tradeoff points obtained by the WMMSE exhibit a bias towards a particular range.



(a) Average sum-rate performance



(b) Average min-rate performance

FIGURE 5. Sum-rate and min-rate performance with respect to P with $K = 6$ and $M_T = 8$.

Next, we assess the scalability in terms of the number of BSs K. Figure 4 presents the performance of various schemes with different K for $M_T = 8$ and $P = 0$ dB. The sum-rate and min-rate maximization tasks are tackled by the WSR and WMR utility functions, respectively. As benchmarks, we consider the naive feature learning (NFL), DBL [28], maximum ratio transmission (MRT), and zero-forcing (ZF) beamforming strategies. The NFL baseline establishes a naive fully-connected neural network for the beam feature DNN $\mathcal{F}_\theta(\cdot)$ which produces the beam features directly. We can see that the proposed method is superior to other baseline methods. It is noted that the NFL, DBL has fixed input/output dimensions, and thus it should be trained at each given K. On the contrary, the proposed scheme trained over $K \in [2, 4]$ outperforms the NFL and DBL method, especially for unseen BS populations $K \geq 5$. This proves the viability of the scalable structure of the proposed DL method. In addition, the proposed decentralized approach exhibits almost identical performance to the centralized WMMSE method [9] which requires extensive calculations. We can attain similar observations from Figure 4(b) where the proposed framework shows little performance loss to the global optimal beamforming solution

TABLE 1. Min-rate.

SNR \ K	2	3	4	5	6
-5dB	99.8	99.8	99.9	99.6	99.4
0dB	99.9	99.8	99.9	99.7	99.5
5dB	99.9	99.8	99.8	99.8	99.7
10dB	101.3	99.9	99.9	99.9	99.8
15dB	102.7	100.2	99.9	99.9	99.8
20dB	103.2	101.1	100.5	100.1	99.8
25dB	105.4	103.2	101.7	100.1	99.9

(a) Sum-rate

SNR \ K	2	3	4	5	6
-5dB	99.7	99.6	99.3	98.2	97.5
0dB	99.3	99.2	98.8	98.2	97.3
5dB	99.3	99.2	98.7	97.8	96.9
10dB	99.3	98.9	98.7	97.4	96.7
15dB	99.2	98.9	98.4	97.4	96.6
20dB	99.2	98.7	98.4	96.9	96.4
25dB	99.1	98.5	97.9	96.7	96.3

(b) Min-rate

produced by the iterative algorithm [7]. The performance gap between the DBL and other benchmark schemes increases as the number of K gets larger, especially in the min-rate performance. DBL presents worse performance than the ZF beamforming solution. These results validate that the proposed DL approach can identify an efficient decentralized beamforming mechanism for an arbitrary K.

Figure 5 examines the scalability with respect to the SNR P for $K = 6$ and $M_T = 8$. The proposed training strategy adopts uniformly generated SNR $P \in \{-5, 0, \cdots, 25\}$ dB. In contrast, the NFL and DBL are required to be optimized at each given P. Nevertheless, the proposed scheme outperforms the DBL and other schemes both in terms of the sum-rate and min-rate performance. Again, the DBL fails to achieve the simple ZF beamforming solutions in all simulated P. It is clear that a direct learning approach is notably inefficient for addressing the complex-valued problem since the number of optimizing variables increases especially in large systems. This proves the effectiveness of the proposed architecture compared to simple fully-connected structures. Thus, we can conclude that the proposed feature learning policy is crucial to learn efficient beamforming vectors in the MISO IC systems.

Table 1 demonstrates the generalization ability of the proposed approach for various K and P. The relative sum-rate and min-rate are defined as the ratio of achieved by the proposed framework to that of the WMMSE and the optimal algorithm performance, respectively. Notice that the results with $K = 6$ correspond to those shown in Figure 5. It is observed that the proposed method performs well over arbitrary combinations of P and K with reduced complexity, thereby proving the scalability. It is interesting to see that for small K and high SNR, the proposed method performs better than the WMMSE method which offers a locally optimum solution for the WSR maximization problem. This indicates the effectiveness of the proposed learning approach to address the nonconvexity of the WSR utility function.

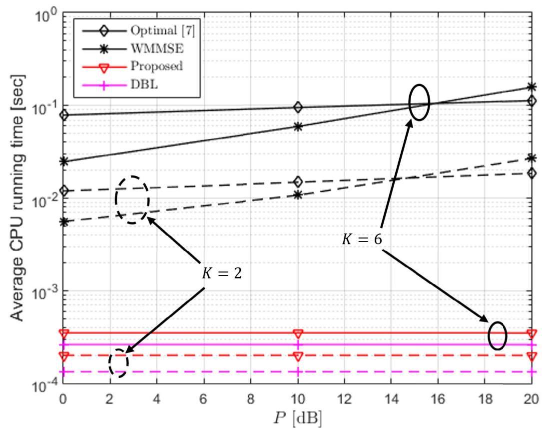


FIGURE 6. Comparison of the average CPU running times.

Figure 6 represents the average CPU execution time of various beamforming schemes with different K and P for $M_T = 8$. For all P and K, the proposed DL method shows almost the same running time, and achieves a substantial reduction in the computation time compared to existing optimization algorithms. The CPU time complexity of the proposed scheme is comparable to that of DBL, owing to the parallel computation ability inherent in the proposed scheme.

VI. CONCLUSION

This paper has proposed a novel DL-based decentralized beamforming framework in MISO IC networks. The proposed learning architecture has been designed such that IT constraint values and dual variables are extracted as the beam features. To learn these parameters, we have leveraged two component DNNs, which are ITNet and DualNet. The ITNet determines the IT constraints that are utilized as backhaul coordination messages among BSs. Utilizing the received messages, the DualNet creates optimized dual variables to control the direction of the beamforming vectors. These component DNNs have been reused at all BSs without loss of optimality, which guarantees the scalability in terms of the number of BSs. We have presented a collaborative training algorithm of the ITNet and DualNet as well as its decentralized implementation strategy. Numerical results have demonstrated the superiority of the proposed framework over existing DL approaches and classical optimization algorithms. For future work, the development of the scalable DNN model with respect to the number of transmit antennas is worth pursuing. One viable approach is to employ GNNs for building component DNNs so that they can process channel vectors of arbitrary length.

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