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Deep learning based adaptive bit allocation for heterogeneous interference channels

Esra Aycan Beyazıt [a,c,*], Berna Özbek [b], Didier Le Ruyet [c]

[a] Electrical and Electronics Engineering Department, Izmir Katip Celebi University, Turkey
[b] Electrical and Electronics Engineering Department, Izmir Institute of Technology, Turkey
[c] Research lab CEDRIC/LAETITIA, Conservatoire National Des Arts Et Métiers, Paris, France

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ABSTRACT

This paper proposes an adaptive bit allocation scheme by using a fully connected (FC) deep neural network (DNN) considering imperfect channel state information (CSI) for heterogeneous networks. Achieving an accurate CSI has a crucial role on the system performance of the heterogeneous networks. Different quantization techniques have been employed to reduce the feedback overhead. However, the system performance cannot increase linearly with the number of bits increasing exponentially. Since optimizing the total number of bits is too complex for the entire network, an initial step is performed to distribute the bits to each cell in the conventional method. Then, the distributed bits are further allocated to each channel optimally. In order to enable direct allocation for the entire network, a FC-DNN based method is presented in this study. The optimized number of bits can be directly obtained for a different number of bits and scenarios by the proposed approach. The simulations are performed by using various scenarios with different allocation schemes. The performance results show that the DNN based method achieves a closer performance to the conventional approach.

1. Introduction

Multiple input multiple output (MIMO) systems in heterogeneous networks are widely studied as a major technology for future wireless communication systems. By equipping a base station (BS) with multiple antennas in a centralized [1] or distributed [2] manner, co-channel interference can be reduced. As a result the total cell throughput can be increased [3]. This potential benefit is mainly obtained by obtaining the channel state information (CSI) at the base stations (BSs).

In frequency division duplexed (FDD) MIMO systems, CSI is acquired at the receiver using feedback methods in which the CSI is sent to the transmitters through feedback channels [4]. In feedback systems, receivers estimate the forward channels by using the pilot signals. After the estimation of the forward channels, receivers quantize the CSI, and feedback it to the transmitters. In order to reduce the feedback overhead, vector quantization approaches have been studied [5,6]. The distortion caused by the quantizaton process can be decreased by increasing the size of the codebook, however this results with the exponentially growth in the feedback overhead. Therefore, the number of bits should be optimized depending on the channel conditions [7].

In the context of heterogeneous networks, there are different studies on the optimization of the bit allocation for limited feedback schemes. The performance of the feedback schemes can be increased by benefiting from the heterogeneous features of the considered network, which are different transmit power levels and unequal number of antennas [8,9]. However, optimizing the total number of bits for the whole network is too complex to fulfill the requirements [10]. In order to find a local optimum, the optimization problems are handled for each cell. In the study of Aycan Beyazit et al. [11], a two-step solution is studied for the adaptive bit allocation scheme in heterogeneous networks. First the total number of feedback bits is shared to each cell considering the transmit powers and the interference levels, then the shared bits are adaptively and locally allocated to each channel in the considered cell. However, as the number of antenna and user increases as in massive MIMO multi-user systems, the complexity of the mentioned technique will even increase.

In this paper, we address the above problem and we propose a data-driven solution for the limited feedback systems through artificial neural networks which is also called deep learning. Recently, deep learning (DL) algorithms have a great attraction in communication systems due to their potentials in pointing out the wireless communication challenges which are nonlinear complex problems. As the data volume increases with the increasing number of users, antennas and base stations, more

* Corresponding author.
E-mail address: esra.aycan@ikcu.edu.tr (E. Aycan Beyazıt).

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strict requirements have to be considered for the next generation communication systems. In order to fulfill these complex requirements, research studies have been focused on artificial intelligence [12,13]. Deep learning based solutions have been studied for different research areas of the communication systems, such as Massive MIMO [14], heterogeneous network [15,16], interference management [17] and mm-Wave [7]. Also some other studies employing DL approaches can be found in the literature, such as radio signal classification [18], resource allocation [19] and compression of the CSI [20,21]. It is worthy of DNN-based FDD networks with limited feedback has been studied in some recent works. For the feedback channels, an extended recurrent neural network (RNN) to jointly optimize the encoding and decoding in the study of Kim et al. [22]. As another study on feedback channels, a joint DNN-based solution is performed to produce both the quantization and the beamforming vectors for homogeneous networks [23].

The main idea of this study is to achieve the direct allocation of the feedback bits to the users so that the initial step which is sharing the bits to each cell first can be eliminated. Since there are many output variables in the training set, supervised learning that learn to affiliate the input data with the output data for a given training set algorithms are suitable for this study [24].

Another property of the training data set of the handled problem is that both the input and output variables are continuous. Therefore, a regression algorithm is trained with a higher number of data obtained with the conventional bit allocation (CBA) scheme as in Aycan Beyazit et al. [11] for several different scenarios. In this study, a fully connected deep neural network (FC-DNN) is used as a regression method since there are multiple number of output variables due to the nature of the MIMO systems.

The main contributions of this study can be listed as follows.

- We propose a DNN based bit allocation learning method for a limited feedback in heterogeneous networks. In particular allocation of the feedback bits can be achieved for the entire network at once by training the DNN. So that the initial step which is the sharing of the bits among the cells can be skipped and the total computational time can be decreased. As a result, the total number of feedback bits can be directly and adaptively allocated to each user equipment (UE) by the proposed DNN based model.
- By exploiting the training data set, the proposed DNN model learns to mimic the system. So that the prediction of the number of bits for each feedback link can be achieved for different total number of bits and also for different heterogeneous network scenarios.
- Extensive simulations are performed in order to evaluate the performance of the proposed method. The obtained results are compared through three different bit allocation schemes considering different scenarios.

The rest of the paper is organized as follows. The system model is explained in Section 2. The proposed DNN-based adaptive bit allocation approach is presented in Section 3 including its structure and training phase. The performance evaluations are given in Section 4. Finally, the study is concluded in Section 5.

Notations: Sets are represented with Capital Greek letters. The transpose conjugate of the matrix $\mathbf{X}$ is given as $(\mathbf{X})^H$ and the determinant of square matrix is shown as $\mathbf{X}$.

2. System model

As a system model, a K-pair heterogeneous network is considered in this study. Under the coverage area of a macro BS, $K-1$ pico BSs are deployed. There are N_{T_k} transmitter antennas at each BS and N_{R_k} receiver antennas at each user. The first pair is determined as macro BS – macro user pair, and the other pairs are pico BS – pico user pairs which are kept in set $k \in \Gamma = \{2, \ldots, K\}$.

The channel matrix between transmitter j and receiver k is denoted as $\mathbf{H}_{kj}$ with dimension $N_{R_k} \times N_{T_j}$. Each element of $\mathbf{H}_{kj}$ is modeled as independent and identically distributed complex Gaussian random variable with $\mathcal{CN}(0,1)$. The received signal at user k is

$$y_k = \sqrt{P_{kk}}\mathbf{H}_{kk}\tilde{\mathbf{T}}_k\mathbf{x}_k + \sum_{\substack{j=1,\\ j\neq k}}^{K}\sqrt{P_{kj}}\mathbf{H}_{kj}\tilde{\mathbf{T}}_j\mathbf{x}_j + \mathbf{n}_k \tag{1}$$

where $\mathbf{n}_k$ is a vector with dimension $N_{R_k} \times 1$ which represents additive white Gaussian noise with zero mean and variance of σ^2. P_k is the transmit power of BS k. P_{kk} is the received power of user k from BS k and the variation of P_{kk} depends on the path loss and shadowing.

$\tilde{\mathbf{T}}_k$ is the precoding matrix of transmitter k with dimension $N_{T_k} \times q_k$ and it is obtained by the IA algorithms under the quantized channel, $\tilde{\mathbf{H}}_{kj}$, between the jth transmitter and the kth receiver with dimension $N_{R_k} \times N_{T_j}$. Independent streams, q_k, are transmitted by BS k where $q_k \leq \min(N_{R_k}, N_{T_k})$.

The decoded data symbols are calculated as $\hat{\mathbf{y}}_k = \tilde{\mathbf{D}}_k\mathbf{y}_k$ where $\tilde{\mathbf{D}}_k$ denotes the postcoding vector of dimension $q_k \times N_{R_k}$.

The actual rate of user k is calculated as follows.

$$\tilde{\mathrm{R}}_k = \log_2(1+\tilde{\gamma}_k) \tag{2}$$

where $\tilde{\gamma}_k$ is the signal to interference noise ratio (SINR) of the kth user. It can be expressed as

$$\tilde{\gamma}_k = \frac{P_{kk}\tilde{\mathbf{d}}_k^H\mathbf{H}_{kk}\tilde{\mathbf{t}}_k\tilde{\mathbf{t}}_k^H\mathbf{H}_{kk}^H\tilde{\mathbf{d}}_k}{\tilde{\mathbf{d}}_k^H\tilde{\mathbf{B}}_k\tilde{\mathbf{d}}_k}, \;\; k = 1, \ldots, K \tag{3}$$

where $\tilde{\mathbf{B}}_k$ is the interference plus noise covariance matrix of the kth receiver and it can be calculated as follows.

$$\tilde{\mathbf{B}}_k = \sum_{j=1, j\neq k}^{K} P_{kj}\mathbf{H}_{kj}\tilde{\mathbf{t}}_j\tilde{\mathbf{t}}_j^H\mathbf{H}_{kj}^H + \sigma^2\mathbf{I}_{N_{R_k}}, \quad k = 1, \ldots, K \tag{4}$$

The actual sum rate is expressed as follows.

$$\tilde{\mathrm{SR}} = \sum_{k=1}^{K}\log_2(1+\tilde{\gamma}_k) \tag{5}$$

In the stream selection based IA algorithms, the set of the selected streams that increases the total sum rate of the network is constructed from the set of available streams. So that the best stream selection scheme is aimed to be found while eliminating the interference by optimizing the precoding and postcoding vectors which are $\tilde{\mathbf{t}}_k$ and $\tilde{\mathbf{d}}_k$, respectively.

3. Proposed DNN based adaptive bit allocation scheme

In this section the problem formulation of the fully connected DNN based bit allocation approach is presented for the limited feedback scheme to generate efficient precoders and postcoders for the stream selection based interference alignment (IA) algorithms. The main objective is to achieve the optimal feedback strategy to maximize the average sum rate by minimizing the rate loss in the considered heterogeneous network.

The rate loss can be minimized by maximizing the actual rate of user k which is calculated by the precoders and postcoders obtained using the quantized channel direction information (CDI).

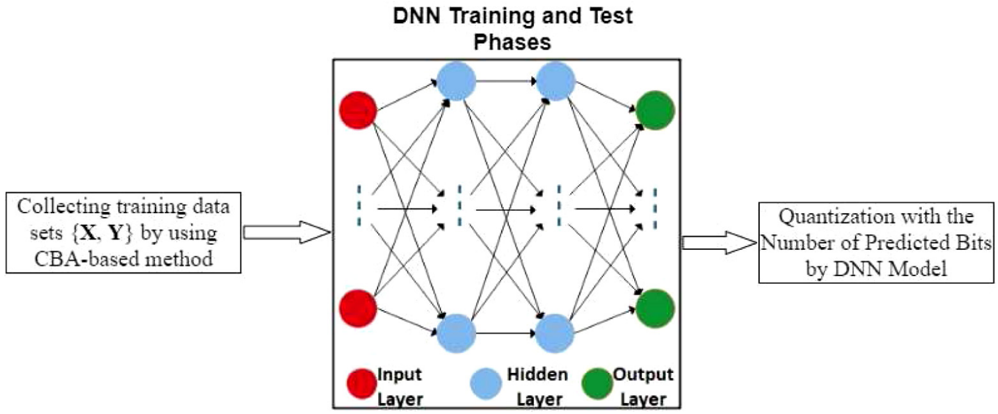


Fig. 1. DNN based bit allocation structure.

3.1. Problem statement

In the CBA method, dynamic bit allocation to each UE can be done by solving the optimization problem for each cell after sharing the total number of bits among the cells. In the proposed approach on the other hand, the total number of bits can be dynamically and directly allocated to each UE considering the entire network. The considered optimization problem can be formulated as follows.

$$\begin{aligned} &\max \mathbb{E}\left[\tilde{\mathrm{R}}_k\right] \\ &\text{s.t.} \sum_{k=1}^{K}\sum_{j=1}^{K} B_{kj} \le B_T \end{aligned} \tag{6}$$

where B_{kj} is the number of bits allocated to the channel between BS j and user k. The total number of feedback bit is $B_T = \sum_{k=1}^{K} B_k$ where B_k is the total number of feedback bits for user k.

To obtain the upper bound for the rate loss for each user, high SINR region is considered for the bit allocation problem [10]. Furthermore, the interfering and the desired channel terms are modeled as independently distributed random variables [5]. Applying Jensen's inequality and using some additional approximations, the optimization problem of the bit allocation for the stream selection based IA algorithms can be expressed in terms of the number of allocated bits, B_{kj}, and received powers, P_{kj}. So that the optimization problem can be rewritten as follows.

$$\begin{aligned} \max_{B_{kj};j=1,\ldots,K} &\left[\log_2\left((P_{kk}/q_k)\left(1-2^{-\frac{B_{kk}}{N_{T_k}N_{R_k}-1}}\right)\right) - \right. \\ &\left.\log_2\left(\frac{P_{kk}(q_k-1)}{q_k}2^{-\frac{B_{kk}}{N_{T_k}N_{R_k}-1}} + \sum_{\substack{j=1\\ j\neq k}}^{K} P_{kj}2^{-\frac{B_{kj}}{N_{T_j}N_{R_k}-1}}\right)\right] \\ &\text{s.t.} \sum_{k=1}^{K} B_{kj} = B_T, \quad \forall j = 1,\ldots,K \end{aligned} \tag{7}$$

3.2. Structure of the proposed bit allocation scheme

For the sake of decreasing the complexity of the quantization process as well as skipping the initial bit allocation to each cell, a DNN for adaptive bit allocation is developed for a limited feedback scheme. The difference with the CBA scheme explained in the above section is that an adaptive bit allocation is achieved for the entire network by training the developed DNN. The flowchart of the proposed bit allocation method and the fully connected DNN architecture can be seen in Fig. 1.

The considered DNN consists of one input, one output and two hidden layers. The output layer is deployed to generate the expected output number of allocated bits to each user.

The details of the training period is explained in Section 3.3. After training the considered DNN model and predicting the number of feedback bits for each user, the desired and the interference channel information is quantized at each UE. The indices of the quantized information are sent back to the transmitters through the feedback channels. Then each transmitter receives codebook indices and reconstructs CSI by using the codebooks that are known at both sides. Afterwards, all the interference CSI are collected at the macro BS and the both the precoders and postcoders are computed by the stream selection based IA algorithms. Then, the calculated vectors are sent from the macro BS to the pico BSs. Each BS forwards the postcoding vectors to the served UEs from the forward link.

3.3. Training the FC-DNN

As a supervised learning method, the training configurations for DNNs are very important. A DNN can learn the relationship between a given set of input data $\mathbf{X} = \left\{x_1,\ x_2,\ \ldots,\ x_N\right\}$ and a given set of labels $\mathbf{Y} = \left\{y_1,\ y_2,\ \ldots,\ y_{N-1}\right\}$ where $N = k^2 + 1$. Every sample in $\mathbf{X}$ is an N-dimensional vector according to the definition of features. The first feature in the input data is the total number of feedback bits, B_T, and other features are composed of k^2 received powers of each users from each BS which is denoted by P_{kj}. Every sample in $\mathbf{Y}$ is an $N-1$ dimensional vector which includes the number of allocated bits to each user. The labels in the training data are obtained by solving the optimization problem of the CBA method using Matlab optimization software.

The activation function used in the model is a logistic sigmoid function defined as $f(x) = \frac{1}{1+e^{-x}}$. In addition, a batch normalization is introduced to each layer. The set of parameters is easily updated by the ADAM algorithm [25]. The mean squared error (MSE) function between the labels and the predicted outputs is employed as the loss function in the training of the considered DNN model.

4. Performance results

In this section, the performance results of the proposed DNN based bit allocation scheme are compared with the ones of the CBA based method utilizing different MIMO heterogeneous network scenarios shown in Fig. 2.

In order to train the proposed DNN model, four different scenarios named as Scenario 1, 2, 3 and 4 are utilized as illustrated in

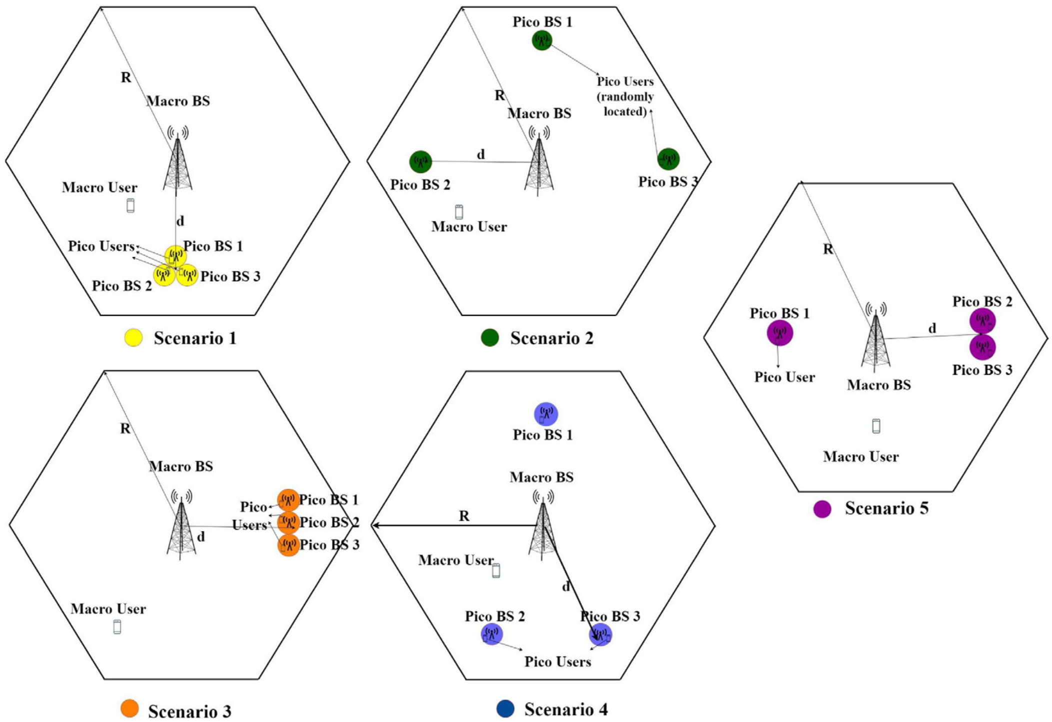


Fig. 2. Considered scenarios for training and prediction phases.

Table 1
Bit allocation schemes for Scenario 1.

Total number of bits, B_T	Allocated number of bits to Macro BS	Allocated number of bits to pico BS 1	Allocated number of bits to pico BS 2 and pico BS 3
$B_T = 48$	$B_1 = 6$	$B_2 = 16$	$B_3 = B_4 = 13$
$B_T = 52$	$B_1 = 7$	$B_2 = 17$	$B_3 = B_4 = 14$
$B_T = 56$	$B_1 = 8$	$B_2 = 18$	$B_3 = B_4 = 15$
$B_T = 60$	$B_1 = 9$	$B_2 = 19$	$B_3 = B_4 = 16$
$B_T = 64$	$B_1 = 10$	$B_2 = 20$	$B_3 = B_4 = 17$
$B_T = 68$	$B_1 = 11$	$B_2 = 21$	$B_3 = B_4 = 18$
$B_T = 76$	$B_1 = 13$	$B_2 = 23$	$B_3 = B_4 = 20$
$B_T = 80$	$B_1 = 14$	$B_2 = 24$	$B_3 = B_4 = 21$
$B_T = 84$	$B_1 = 15$	$B_2 = 25$	$B_3 = B_4 = 22$
$B_T = 88$	$B_1 = 16$	$B_2 = 26$	$B_3 = B_4 = 23$
$B_T = 92$	$B_1 = 17$	$B_2 = 27$	$B_3 = B_4 = 24$
$B_T = 100$	$B_1 = 19$	$B_2 = 29$	$B_3 = B_4 = 26$
$B_T = 104$	$B_1 = 20$	$B_2 = 30$	$B_3 = B_4 = 27$
$B_T = 108$	$B_1 = 21$	$B_2 = 31$	$B_3 = B_4 = 28$
$B_T = 112$	$B_1 = 22$	$B_2 = 32$	$B_3 = B_4 = 29$
$B_T = 116$	$B_1 = 23$	$B_2 = 33$	$B_3 = B_4 = 30$
$B_T = 120$	$B_1 = 24$	$B_2 = 34$	$B_3 = B_4 = 31$

Fig. 2. In the given figure, each scenario is demonstrated with different color and the colored circles show the pico cells. Scenario 5 shown in the figure is utilized as the predicted scenario.

For all the scenarios, the macro BS is located at $(0, 0)$ and the macro user is uniformly randomly located within the cell. The ratio d/R is calculated to identify the pico cell locations where d is the distance between the macro and pico BSs and R is radius of the macro cell. Since, pico cells are generally deployed at the edge areas of the macro cell in practice, the ratio d/R is chosen as 0.6, 0.7 and 0.8. In each scenario, there are 3 pico BSs and 1 macro BS. The number of transmit antennas is 2 for each pico BS and 4 for the macro BS. Each BS serves only one user that is randomly placed inside the coverage area of the related BS. The number of receive antennas is 2 at each UE. Simulation parameters can be found in the study of Aycan Beyazit et al. [11].

Both the training and test data sets are obtained with the first four scenarios shown in Fig. 2. In order to evaluate the performance of the proposed DNN-based approach comparatively, we define different allocation schemes denoted as CBA BAS-1, CBA BAS-2 and equal bit allocation (EBA). The details are given as follows.

- CBA BAS-1: Using the outcome of the study in Aycan Beyazit et al. [11], B_T is first shared among all the cells by allocating more bits to pico cells than the macro cell. Later, for each cell, bits are distributed to the channels between each BS and each user by solving the optimization problem defined by Eq. (7).
- CBA BAS-2: B_T is first equally shared among all the cells. Then the optimization problem defined in Eq. (7) is solved and the number of bits are obtained for each channel.
- EBA: B_T is shared among all the channels between BSs and UEs equally. Since there are 16 channels in the considered scenarios, the performance of EBA is given for B_T values which are multiples of 16. The number of allocated bits to each user is $B_{kj} = B_T/16$, $\forall j = 1, \dots, K$.

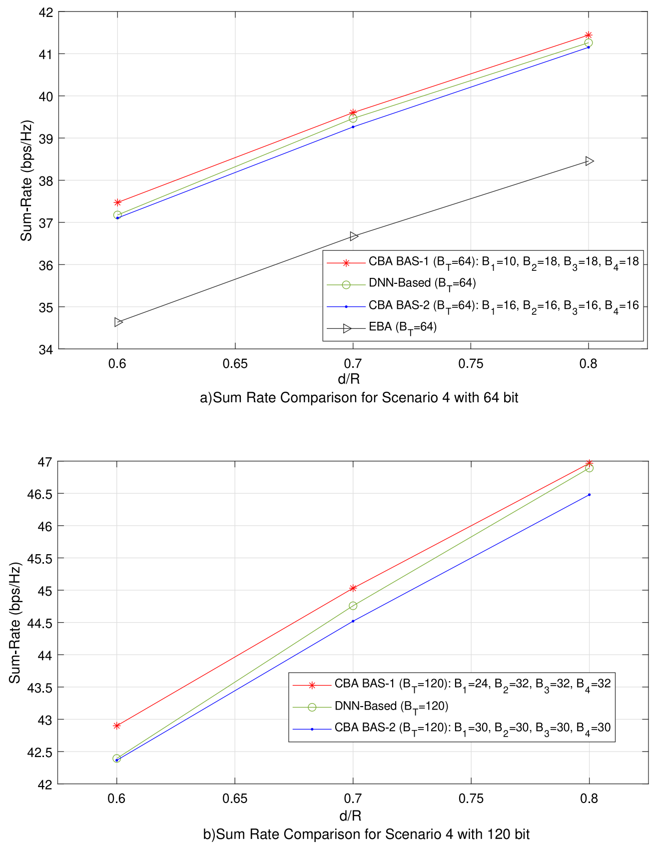


Fig. 3. Sum rate comparison for Scenario 4 with 64 and 120 bits.

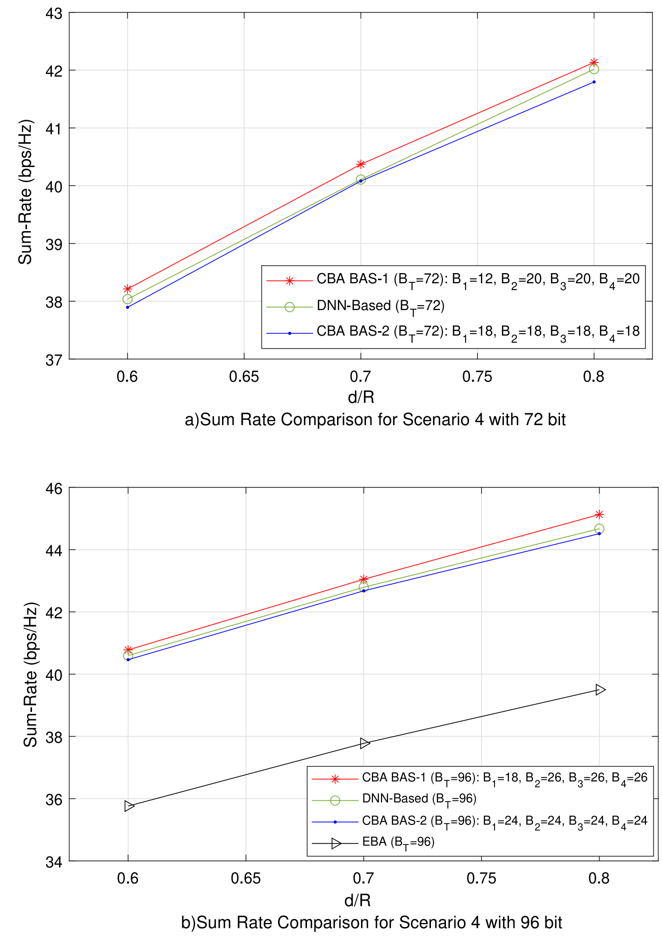


Fig. 4. Sum rate comparison for Scenario 4 with 72 and 96 bits.

Table 2
Bit allocation schemes for Scenario 2, 3 and 4.

Total number of bits, B_T	Allocated number of bits to Macro BS	Allocated number of bits to pico BSs 1, 2 and 3
$B_T = 48$	$B_1 = 6$	$B_2 = B_3 = B_4 = 14$
$B_T = 52$	$B_1 = 7$	$B_2 = B_3 = B_4 = 15$
$B_T = 56$	$B_1 = 8$	$B_2 = B_3 = B_4 = 16$
$B_T = 60$	$B_1 = 9$	$B_2 = B_3 = B_4 = 17$
$B_T = 64$	$B_1 = 10$	$B_2 = B_3 = B_4 = 18$
$B_T = 68$	$B_1 = 11$	$B_2 = B_3 = B_4 = 19$
$B_T = 76$	$B_1 = 13$	$B_2 = B_3 = B_4 = 21$
$B_T = 80$	$B_1 = 14$	$B_2 = B_3 = B_4 = 22$
$B_T = 84$	$B_1 = 15$	$B_2 = B_3 = B_4 = 23$
$B_T = 88$	$B_1 = 16$	$B_2 = B_3 = B_4 = 24$
$B_T = 92$	$B_1 = 17$	$B_2 = B_3 = B_4 = 25$
$B_T = 100$	$B_1 = 19$	$B_2 = B_3 = B_4 = 27$
$B_T = 104$	$B_1 = 20$	$B_2 = B_3 = B_4 = 28$
$B_T = 108$	$B_1 = 21$	$B_2 = B_3 = B_4 = 29$
$B_T = 112$	$B_1 = 22$	$B_2 = B_3 = B_4 = 30$
$B_T = 116$	$B_1 = 23$	$B_2 = B_3 = B_4 = 31$
$B_T = 120$	$B_1 = 24$	$B_2 = B_3 = B_4 = 32$

The B_T values in the training data set is listed in Tables 1 and 2.

In Scenario 1, Pico BS 1 is closer to Macro BS than the other two pico BSs. Since the interference generated from macro BS to pico BS 1 user is stronger, more bits are required for the channels of Pico BS 1 user in the limited feedback case. Therefore, the bit allocation schemes for Scenario 1, the number of bits allocated to each user, B_k, $k = 1, \ldots, 4$, are listed in Table 1.

For Scenario 2, 3 and 4, it can be seen that each pico BS has the same distance to the macro BS. Therefore, equal number of feedback bits is given to the channels of the pico BS users. The bit allocation schemes for Scenario 2, 3 and 4 the number of bits allocated to each user, B_k, $k = 1, \ldots, 4$, are given in Table 2.

Table 3
Training parameters.

Hyper-parameter	Setting
Processing cell	2 Hidden Layer
Hidden nodes per layer	50
Number of test data	3,06,000
Number of training data	9,18,000
Optimizer	Adam
Batch size	200
Epochs	10^3
Initial learning rate	0.0003

Note that B_1 is the number of allocated bits for the macro cell, B_2 is for pico cell 1, B_3 for pico cell 2 and B_4 for pico cell 3.

There are training set of 4500 samples and test set of 1500 samples for each of the four training scenarios. In each scenario, we consider 18 different bit allocation schemes and three d/R values. Therefore, the total number of training data is 918,000 and the number of test data is 306,000.

The predictions are carried out for both Scenario 4 and Scenario 5 for the total number of bits with $B_T = 64$, $B_T = 72$, $B_T = 96$, $B_T = 120$, $B_T = 128$ and $B_T = 140$.

For Scenario 4, $B_T = 64$ and $B_T = 120$ are in the training data set while $B_T = 72$, $B_T = 96$, $B_T = 128$ and $B_T = 140$ values are not in the training data set. In addition, the data regarding to scenario 5 is not included in the DNN training phase.

Throughout all experiments, a relatively reasonable hyper-parameter setting is chosen as listed in Table 3.

4.1. Performance over fixed locations of UEs with different B_T values

In order to evaluate the performance of the DNN based bit allocation with a different B_T, Scenario 4 is utilized where P_{kj}, $\forall k, j = 1, \ldots, 4$ values are included in the training data set.

The performance comparisons of the DNN-based bit allocation, the CBA and EBA schemes are examined for 3 different cases.

4.1.1. Case 1: Performance results of B_T values that are in the training data set

In the first case, the performance comparisons of different bit allocation schemes for $B_T = 64$ and $B_T = 120$ which are included in the training data set are shown in Fig. 3 in terms of the sum rate.

It can be seen that the performance of the proposed method for both $B_T = 64$ and $B_T = 120$ is between the performances of the CBA BAS-1 and CBA BAS-2 approaches. Thus, the proposed approach almost achieves the sum-rate values of the optimized bit allocation schemes. The gray curve represents the performance of EBA in which the number of allocated bits is 4 for each channel. The sum-rate values of EBA is 2.75 bps/Hz lower than the sum-rate values of the DNN-based approach on average.

4.1.2. Case 2: Performance results of B_T values that are not in the training data set

For the second case, the performance comparisons of different bit allocation schemes for $B_T = 72$ and $B_T = 96$ which are not in the training data set are given in Fig. 4 in terms of the sum rate.

It can be observed that the behavior of the DNN based bit allocation schemes for $B_T = 72$ and $B_T = 96$ are similar with the one obtained for $B_T = 64$ and 120. Therefore it can be said that the DNN based method can achieve good performances even for the data which is not in the training data set. In addition, by implementing the DNN-based method, there is an improvement of 5.2 bps/Hz on average in the sum-rate values when compared to the EBA approach.

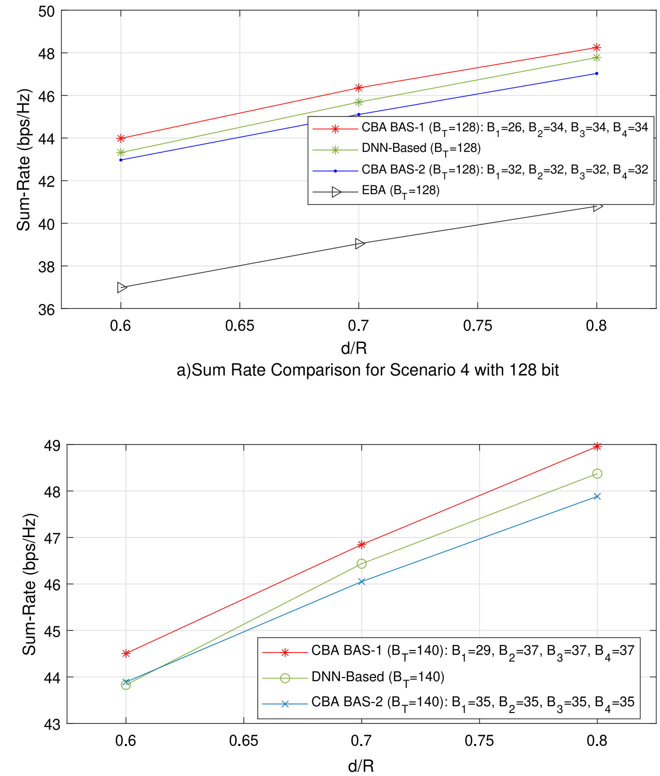
4.1.3. Case 3: Performance results for B_T that are out of B_T values range in the training data set

The third case evaluates the performance of the DNN based model for B_T values which are out of B_T values range in the training data set. For example, the performances are compared for $B_T = 128$ and $B_T = 140$ values in Fig. 5.

Once again it can be seen that the DNN based model can reproduce the behavior of the optimized CBA schemes for even the bit allocation schemes which are not in the range of B_T values in the training data set. Also, for $B_T = 128$ condition, DNN-based method has a gain of 6 bps/Hz on average in the sum-rate values when compared to the EBA approach. As a result, the proposed approach has a performance closer to the CBA BAS-1 bit allocation by eliminating the initial bit sharing step which is a cumbersome task.

4.2. Performance over different locations of UE with different B_T values

Another different prediction is performed with a new scenario to observe the learning performance of the proposed DNN-based model with different P_{kj}, $\forall k, j = 1, \ldots, 4$ values which are not included in the training data set. The training is performed using the 4 reference scenarios while the scenario 5 is used for the prediction. Different bit allocation schemes are performed with $B_T = 64$, $B_T = 72$, $B_T = 98$, $B_T = 120$, $B_T = 128$ and $B_T = 140$ for this scenario. As in Scenario 4 performance evaluations, the performance comparisons between the DNN-based and the CBA-based schemes are given in 3 cases for the predicted scenario, Scenario 5.



a)Sum Rate Comparison for Scenario 4 with 128 bit

b)Sum Rate Comparison for Scenario 4 with 140 bit

Fig. 5. Sum rate comparison for Scenario 4 with 128 and 140 bits.

4.2.1. Case 1: Performance results of B_T values that are in the training data set

In the first case, the B_T values included in the training data set are considered, such as $B_T = 64$ and $B_T = 120$. The performances are shown in Fig. 6 in terms of the sum rate.

Similar to the results obtained with Scenario 4, the performance of the proposed approach is between the CBA BAS-1 and CBA-BAS-2 methods when $B_T = 64$ and $B_T = 120$.

4.2.2. Case 2: Performance results of B_T values that are not in the training data set

As the second case in which the B_T values not in the training data set, such as $B_T = 72$ and $B_T = 96$, the performance comparisons of different bit allocation schemes are illustrated in Fig. 7.

In the given graphic, for $B_T = 72$, the performance of the DNN-based approach is very close to the performance of CBA BAS-1 approach. For $B_T = 96$, it can be observed that the behavior of the DNN-based bit allocation scheme is similar with the one obtained in $B_T = 72$ case. Additionally, considering the performance results of the DNN-based method, it can be observed that the sum-rate values are approximately 4.45 bps/Hz better than the sum-rate values obtained by the EBA method.

4.2.3. Case 3: Performance results for B_T that are out of B_T values range in the training data set

In the third case, $B_T = 128$ and $B_T = 140$ values are utilized for the performance evaluations for B_T values ranged outside the trained B_T values. The performance results are given in Fig. 8.

In Fig. 8, for $B_T = 128$ case, the DNN-based method has an improvement of 6 bps/Hz on average in the sum-rate values comparing to the EBA scheme. Also the DNN-based method has a gain of 0.29 bps/Hz when compared to the CBA BAS-2. Moreover, the

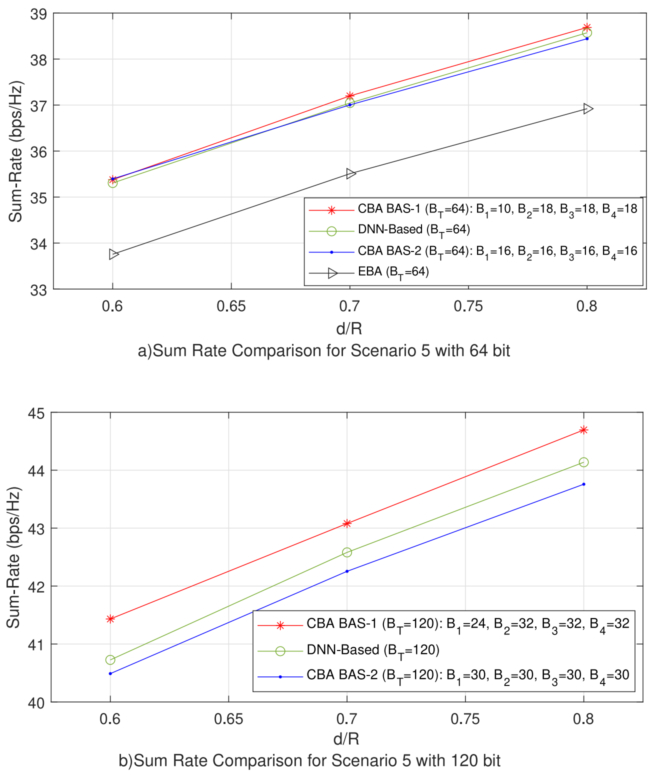


Fig. 6. Sum rate comparison for Scenario 5 with 64 and 120 bits.

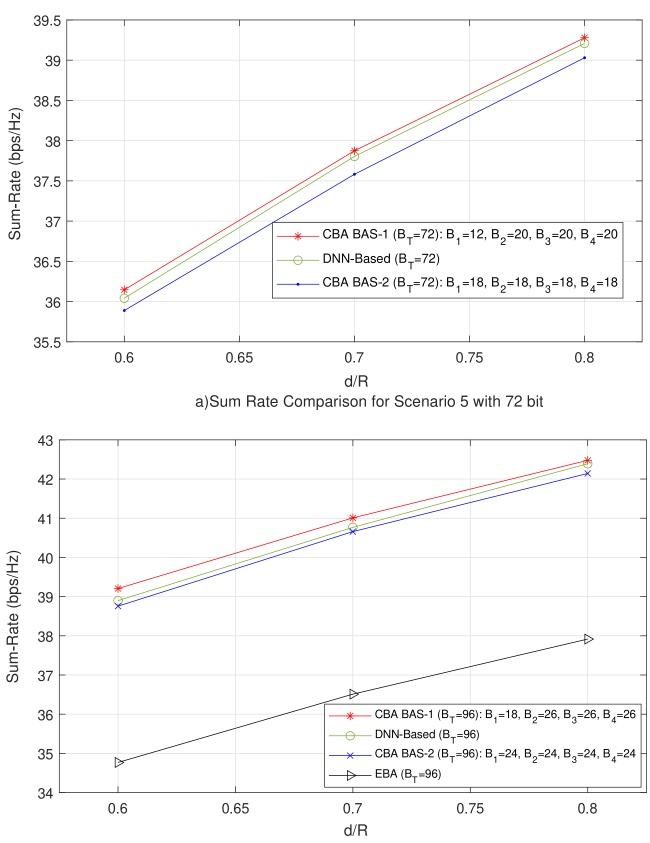


Fig. 7. Sum rate comparison for Scenario 5 with 72 and 96 bits.

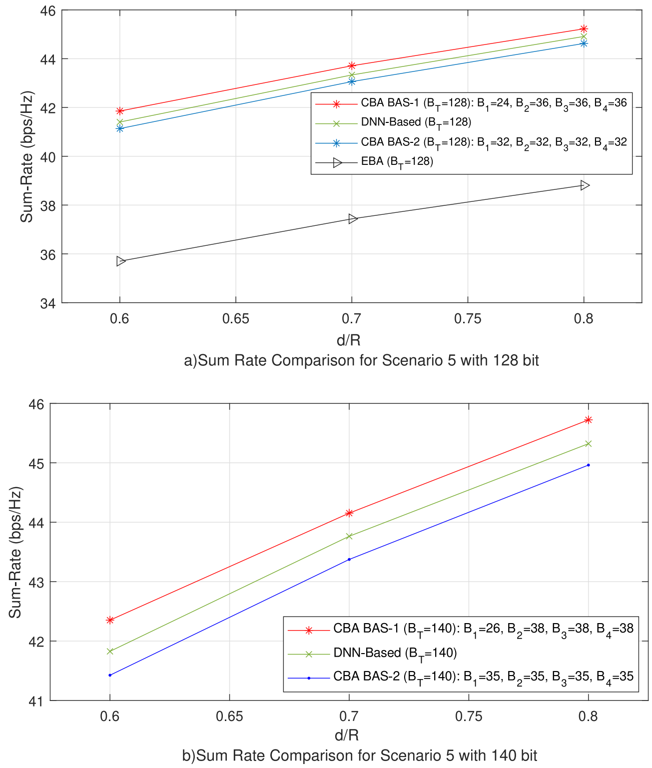


Fig. 8. Sum rate comparison for Scenario 5 with 128 and 140 bits.

Table 4
The average number of allocated bits for $B_T = 64$ case obtained by CBA based method in Scenario 5.

$B_{11} = 5.15$	$B_{21} = 1.48$	$B_{31} = 1.62$	$B_{41} = 1.75$
$B_{12} = 3.26$	$B_{22} = 13.16$	$B_{32} = 1.58$	$B_{42} = 0$
$B_{13} = 3.47$	$B_{23} = 1.32$	$B_{33} = 13.21$	$B_{43} = 0$
$B_{14} = 3.56$	$B_{24} = 0$	$B_{34} = 0$	$B_{44} = 14.44$

Table 5
The average number of allocated bits for $B_T = 64$ case obtained by DNN based method in Scenario 5.

$B_{11} = 5.22$	$B_{21} = 1.14$	$B_{31} = 1.27$	$B_{41} = 0.94$
$B_{12} = 3.62$	$B_{22} = 14.54$	$B_{32} = 0.76$	$B_{42} = 0.81$
$B_{13} = 3.20$	$B_{23} = 0.53$	$B_{33} = 13.74$	$B_{43} = 0.46$
$B_{14} = 3.07$	$B_{24} = 0.11$	$B_{34} = 0.94$	$B_{44} = 13.92$

difference between the CBA BAS-1 and the DNN-based methods is 0.31 bps/Hz. For $B_T = 140$, on the other hand, similarly, the performance of the proposed approach is between the CBA BAS-1 and CBA BAS-2. Depending on these results, it can be said that the DNN-based bit allocation approach is an effective approach even for different scenarios and different B_T values which are not utilized for the training phase of the DNN model.

For $B_T = 64$ case, the average number of allocated bits obtained by the CBA and the DNN-based methods for pico cell locations at $d/R = 0.6$ are given in Tables 4 and 5, respectively. It can be observed that the average number of allocated feedback bits to each user both in the CBA-based and DNN-based methods are very close to each other. These results validate the use of DNN-based method for adaptive bit allocation. Moreover, the allocation of a given number of total bits is achieved for each user without an additional step which is in the CBA-method.

The performance of the DNN model is evaluated with different metrics such as Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) which are defined as follows [24].

Table 6
Performance of the DNN training model.

Evaluation metrics for DNN	For $B_T = 64$	For $B_T = 72$	For $B_T = 96$	For $B_T = 128$	For $B_T = 140$
RMSE	0.032	0.031	0.030	0.031	0.031
MAE	0.020	0.019	0.019	0.019	0.019

- RMSE $= \sqrt{1/n \sum_{i=1}^{n} (O_i - S_i)^2}$
- MAE $= 1/n \sum_{i=1}^{n} |(O_i - S_i)|$

where O_i denotes each of the observed values, S_i denotes each of the predicted values, and n is the number of observations.

The results are given in Table 6 obtained for Scenario 5 with $B_T = 64$, $B_T = 72$, $B_T = 96$, $B_T = 128$ and $B_T = 140$.

For both metrics, the error term is minimized as the score is close to 0. Therefore, it can be said that the values predicted by the proposed DNN model are reliable.

5. Conclusion

In this study, a deep learning approach is proposed to achieve the feedback bit allocation to each user by using the output of the CBA scheme as the training data set. It has been shown that the DNNs can be collaboratively used to obtain an efficient solution to the bit allocation problem which has higher computational complexity for interference alignment with limited feedback in heterogeneous networks. Directly allocation of the total number of bits to each user is achieved by the proposed DNN-based bit allocation solution with a closer performance to the CBA-based approach for different heterogeneous network scenarios. As a result, a lightweight solution for bit allocation is proposed for different scenarios with different total number of feedback bits by training the DNN model. Improving the training of the proposed DNN-based method is one of the possible future works.

CRediT authorship contribution statement

Esra Aycan Beyazıt: Methodology, Conceptualization, Realization, Writing. **Berna Özbek:** Methodology, Guidance, Writing - review & editing. **Didier Le Ruyet:** Methodology, Guidance, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Esra Aycan Beyazıt is an Assistant Professor in telecommunication field with the Electrical and Electronics Engineering Department, Izmir Katip Celebi University, Izmir, Turkey. She received her B.Sc. degree in Electrical and Electronics Engineering from Dumlupınar University in 2005; and her M.Sc. degree in Computer Engineering from İzmir Institute of Technology in 2008. She received her Ph.D. degree in the area of Telecommunications from both İzmir Institute of Technology and Conservatoire National des Arts et Métiers in 2016 after completing Coutelle Ph.D. program. She worked as a research assistant at Electrical and Electronics Engineering Department of İzmir Institute of Technology during her Ph.D. studies.

She also has industrial experience of more than 3 years. Her research interests are interference management, limited feedback links, heterogeneous networks and artificial intelligence.

Berna Özbek (Senior Member, IEEE) is currently an Associate Professor in telecommunication with the Electrical and Electronics Engineering Department, Izmir Institute of Technology, Turkey. She has been awarded as a Marie-Curie Intra-European (EIF) Fellow by European Commission in 2010. She has coordinated one international and four national projects, served as a consultant for three Eureka-Celtic projects and three industry driven projects. Under her supervision, 15 master thesis and two Ph.D. dissertations have been completed and is currently supervising three PhD. She has published more than 90 peer-reviewed articles, one book, one book chapter, and two patents. Her research interests include interference management, resource allocation, limited feedback links, device-to-device communications, physical layer security, massive MIMO, NOMA and mmWave communications.

Didier Le Ruyet (Senior Member, IEEE) received the Eng. and Ph.D. degrees from the Conservatoire National des Arts et Métiers (CNAM) in 1994 and 2001, respectively, and the Habilitation à diriger des recherches from Paris XIII University in 2009. From 1988 to 1996, he was a Senior Member of the Technical Staff at SAGEM Defence and Telecommunication, France. He joined CNAM, Paris, as a Research Assistant, in 1996. From 2002 to 2010, he was an Assistant Professor with the Electronic and Communication Laboratory, CNAM. Since 2010, he has been a Full Professor with the CEDRIC Research Laboratory, CNAM. He has published about 200 papers in refereed journals and conference proceedings and nine books/book chapters in the area of communication. He has been involved in different National and European projects dealing with multicarrier transmission techniques and multi-antenna transmission. His main research interests lie in the areas of digital communications and signal processing, including channel coding, detection and estimation algorithms, filter bank-based multi-carrier communication, and multi-antenna transmission. He has served as a Technical Program Committee member in major IEEE conferences.