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DNN-based algorithm for joint SIC ordering and power allocation in downlink NOMA-enabled heterogeneous networks

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Abstract

In the heterogeneous network (HetNet) employing downlink non-orthogonal multiple access (NOMA), we focus on the non-convex optimization problem to optimize the spectral efficiency (SE) while the users satisfy the quality-of-service (QoS) requirement. In the previous work, the optimal joint successive interference cancellation and power allocation (JSPA) algorithm for maximizing SE is proposed to solve the mixed-integer non-linear programming (MINLP) problem in NOMA-enabled HetNet. However, the optimal solution requires exponential complexity by the number of base stations (BSs). Therefore, we present a deep neural network (DNN)-based algorithm for JSPA to reduce the complexity. In particular, to deal with the MINLP-based JSPA problem, we reformulate it into an equivalently simple problem that optimizes only the power consumption of BSs. Then, we introduce the unsupervised DNN-based method for JSPA to handle the simplified problem. The presented scheme yields improved SE and outage performance compared with traditional DNN-based methods. Additionally, we propose a user selection scheme with low complexity to enhance the SE of the proposed DNN-based power allocation. Through simulations, we illustrate that the suggested DNN-based scheme can attain SE performance similar to that of the optimal scheme.

Keywords: Non-orthogonal multiple access; Heterogeneous network; Deep learning; Successive interference cancellation; Power allocation; Spectral efficiency

1. Introduction

As non-orthogonal multiple access (NOMA) utilizes superposition coding and successive interference cancellation (SIC), it has provided high compatibility with various techniques such as a heterogeneous network (HetNet) and a multiple-input multiple-output (MIMO) system [1–4]. In addition, NOMA has been considered to improve the spectral efficiency (SE). In [5], the power allocation (PA) problem to maximize spectral efficiency (SE) in single-cell NOMA is demonstrated as a convex, and the authors present the closed-form expression of the optimal PA coefficient (PAC). However, in multi-cell NOMA, resource allocation algorithms should designed to better manage inter-cell interference between cells as well as intra-cell interference between users in a cell, different from the single-cell NOMA [2]. Specifically, in multi-cell NOMA, the SIC decoding order for NOMA depends on signal-to-interference-plus-noise-ratios (SINRs) instead of the channel-to-noise-ratios [6], and the PA problem is shown to be non-convex and strongly NP-hard. Hence, identifying a global optimal solution for multi-cell NOMA poses a challenge. Therefore, in [6], using the optimal PACs in [5], the optimal solution of joint SIC and PA (JSPA) problem for maximizing total SE is proposed by exploring algorithm. As compared to existing algorithms for multi-cell NOMA, the JSPA scheme can reduce the computational complexity while achieving optimal performance, but its complexity is still an exponentially increasing function of the number of base stations (BSs) due to its exploration algorithm. Moreover, it is challenging to present an alternative method to reduce the exponential complexity, since the JSPA problem for SE maximization is categorized as a mixed-integer non-linear programming (MINLP). Especially, the complexity issue of the JSPA problem may be crucial for an NOMA-enabled HetNet because it contains multiple small cells. It is noted that since the NOMA-enabled HetNet can

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support massive connectivity, it can be suitable for the practical applications of massive Internet-of-Things and ultra-dense networks [1].

To cope with this high complexity issue in multi-cell scenarios, the deep learning (DL) techniques are presented in [4,7]. Especially, in [7,8], using the deep neural network (DNN)-based training method, the DL-based resource allocation algorithms are proposed to enhance the system performance without any iterative and exploratory algorithm. Therefore, the DL-based schemes are widely used with their specific training methods, e.g., supervised, unsupervised, and reinforcement learning algorithms, as in [4,7,8]. However, since the supervised and reinforcement learning schemes involve the labeled data generation and trial-and-error problems for training, respectively, those schemes can induce high training complexity. On the other hand, the *unsupervised learning* scheme can achieve considerably lower training complexity compared with those methods because it uses the predefined loss function for training. Therefore, the unsupervised learning algorithm can be an appropriate solution for complex resource allocation problems such as the JSPA problem.

Although unsupervised learning-based approaches have been validated to enhance SE performance and reduce the complexity of training and testing, the conventional studies in [3,7] may not obtain the desired performance, due to the highly complicated MINLP problem for JSPA in NOMA-based HetNets. To tackle this issue, in this paper, we equivalently simplify the JSPA problem using a mathematical analysis based on optimal PA in [6]. Since the simplified problem optimizes only the power consumption coefficients (PCCs) of BSs, it can be effectively applied to an unsupervised learning mechanism compared with the conventional approaches to optimize joint PCCs and PACs. Thus, in this paper, a low-complexity JSPA scheme is proposed in downlink NOMA-enabled HetNets with multiple cells, where the unsupervised learning approach is used for SE maximization while maintaining the quality-of-service (QoS) requirement.

The main contributions of this paper are listed as follows:

- We present a simplified JSPA problem for downlink NOMA-enabled HetNets, where the optimal PA analysis is used.
- We propose an unsupervised DNN-based JSPA scheme to resolve the simplified JSPA problem, where the proposed scheme can find the pertinent PCCs for BSs (i.e., transmit powers at BSs) with lower complexity than the conventional JSPA algorithm in [6].
- We present a loss function for training the PCCs of BSs in the proposed scheme, which is newly defined for SE maximization while satisfying the QoS requirement based on the simplified JSPA problem.
- We introduce a user selection algorithm to select users that maintain the QoS requirement. The proposed user selection scheme does not require any exhaustive search or iterative operations, whereas the conventional schemes for optimizing joint user selection and PA are based on exhaustive search or iterative algorithms [9,10].

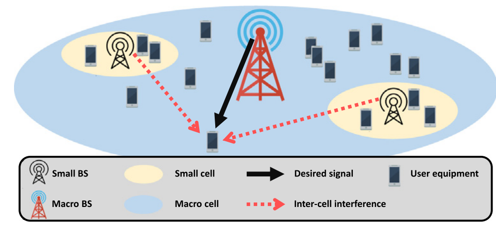

Fig. 1. An illustration of downlink NOMA-based HetNet.

In our training algorithm, it is noted that the PACs for NOMA are obtained by the closed-form expression of optimal PACs for single-cell NOMA in [5] because the non-convex optimization problem for multi-cell NOMA becomes a convex problem when the PCCs of BSs are determined by the proposed unsupervised DNN. Moreover, from the proposed loss function-based training method, we can jointly optimize the SIC decoding order and PA.

2. System model

As in Fig. 1, the downlink NOMA-based HetNet is considered, which consists of a macro BS, $B-1$ small BSs, and U users within the macro and small cells. We assume that all the BSs use the same frequency band for data communications that experience path loss and flat fading, where all the BSs and users are equipped with a single antenna. In addition, through optical cables or reliable wireless backhaul links, the macro BS can acquire perfect information about all the channel gains for users in the macro and small cells. The set of all BSs is $\mathcal{B} = \{1, 2, \ldots, b, \ldots, B\}$, and the set of all users is $\mathcal{U} = \{1, 2, \ldots, u, \ldots, U\}$. Let us denote α, $g_{b,u} \sim \mathcal{CN}(0, 1)$, and $d_{b,u}$ as the path loss exponent, the distance between BS b and user u, and the Rayleigh fading component, respectively. Then, the channel power of user u which is associated with BS b is $h_{b,u} = |g_{b,u}|^2 d_{b,u}^{-\alpha}, \forall b \in \mathcal{B}, \forall u \in \mathcal{U}$.

The users are associated with the BS that achieves the maximum SINR based on path loss, i.e., $\max_{b\in\mathcal{B}} \{\Gamma_{b,u}\}$, where $\Gamma_{b,u}$ is the path loss-based SINR, and it is obtained as $\Gamma_{b,u} = \frac{d_{b,u}^{-\alpha} P_b^{max}}{\sum_{i\in\mathcal{B}\setminus\{b\}} d_{i,u}^{-\alpha} P_i^{max} + \sigma^2}$. Moreover, P_b^{max} and σ^2 are the maximum power of BS b and the noise power, respectively. Let the user association index between BS b and user u be denoted as $x_{b,u}$, and thus when $b = \arg\max_{i\in\mathcal{B}}\{\Gamma_{i,u}\}$, $x_{b,u} = 1$, but $x_{i,u} = 0$ for $i \in \mathcal{B}\setminus b$. Then, each BS transmits data signals to the associated users (i.e., users satisfying $x_{b,u} = 1$) using NOMA, where the users' signals are simultaneously transmitted with different powers.

In the NOMA-based HetNet, all the users suffer from two types of interference: the inter-cell interference from neighboring BSs and the intra-cell interference caused by NOMA transmissions at a serving BS. Letting the set of users associated with BS b be denoted as $\mathcal{M}_b$, i.e., $x_{b,u} = 1$. The binary decoding decision indicator $\lambda_{b,m,k} \in \{0, 1\}, \forall m, k \in \mathcal{M}_b$ becomes 1 if the signal of kth user is regarded as the interference at user m. Otherwise, if $\lambda_{b,m,k} = 0$, user m fully decodes the signal of kth user. Moreover, because of the nature of the SIC decoding order, the decoding indicator should maintain, $\lambda_{b,m,k}+\lambda_{b,k,m}=1$, $\lambda_{b,m,k}\lambda_{b,k,i}\leq\lambda_{b,m,i}$, and $\lambda_{b,m,m}=1$ [6]. Consequently, letting the set of associated users whose signals are not cancelled by SIC at user $m\in\mathcal{M}_b$ be denoted as $\Phi_{b,m}=\{k\in\mathcal{M}_b\backslash\{m\}|\lambda_{b,m,k}=1\}$, the intra-cell interference power between BS b and user m is given by $N_{b,m}=\sum_{j\in\Phi_{b,m}}p_{b,j}h_{b,m}$, where $p_{b,j}$ is the PAC of user j at BS b for NOMA transmissions. On the other hand, the inter-cell interference power at user m associated with BS b is expressed as $I_{b,m}=\sum_{i\in\mathcal{B}\backslash\{b\}}\sum_{j\in\mathcal{M}_b}p_{i,j}h_{i,m}$. Therefore, assuming perfect SIC for decoding, we can obtain the achievable SE for user m in the NOMA-enabled HetNet as

$$R_{b,m}=\log_2\left(1+\frac{h_{b,m}p_{b,m}}{N_{b,m}+I_{b,m}+\sigma^2}\right),\forall b\in\mathcal{B},\forall m\in\mathcal{M}_b. \tag{1}$$

In this paper, we aim to optimize the JSPA problem for total SE maximization while each user meets the minimum SE requirement, denoted as R_{min}, which is formulated as

$$\max_{\forall p_{b,m},\forall\lambda_{b,k,m}}\sum_{b\in\mathcal{B}}\sum_{m\in\mathcal{M}_b}R_{b,m}, \tag{2a}$$

$$\text{s.t.}\quad \sum_{m\in\mathcal{M}_b}p_{b,m}\leq P_b^{max},\qquad \forall b\in\mathcal{B}, \tag{2b}$$

$$R_{b,m}\geq R_{min},\qquad \forall b\in\mathcal{B},\forall m\in\mathcal{M}_b, \tag{2c}$$

$$\lambda_{b,m,k}+\lambda_{b,k,m}=1,\quad \forall b\in\mathcal{B},\forall m,k\in\mathcal{M}_b, \tag{2d}$$

$$\lambda_{b,m,k}\lambda_{b,k,i}\leq\lambda_{b,m,i},\forall b\in\mathcal{B},\forall m,k,i\in\mathcal{M}_b, \tag{2e}$$

$$\lambda_{b,m,m}=1,\qquad \forall b\in\mathcal{B},\forall m\in\mathcal{M}_b, \tag{2f}$$

where (2b) suggests that the sum of PACs cannot exceed $P_b^{max},\forall b\in\mathcal{B}$, and (2c) is the constraint of the QoS requirement. Finally, the constraints in (2d), (2e), and (2f) correspond to the constraints of SIC decoding order. We assume that if any user in the HetNet violates the minimum SE requirement, the outage event occurs.

3. Proposed DNN-based SIC ordering and PA algorithm

3.1. Training algorithm for DNN-based JSPA

To solve the MINLP problem in (2), we first reformulate it into an equivalently simple problem that optimizes only the PCC on BS. It is noted that the PCC refers to the normalized total transmit power at the BS, which can be expressed as follows:

$$a_b=\frac{\sum_{m\in\mathcal{M}_b}p_{b,m}}{P_b^{max}},\forall b\in\mathcal{B}, \tag{3}$$

where $0\leq a_b\leq 1$ due to the constraint in (2b). Specifically, it is noted that if the PCCs are predetermined, the optimal decision of SIC decoding order and the closed expression of optimal PACs for NOMA-based HetNet can be determined, where the SIC decoding order is based on instantaneous SINRs [6]. Letting the instantaneous SINR between BS b and user m be denoted as $\gamma_{b,m}$, the SINRs are obtained as

$$\gamma_{b,m}=\frac{h_{b,m}a_bP_b^{max}}{I_{b,m}+\sigma^2},\forall b\in\mathcal{B},\forall m\in\mathcal{M}_b. \tag{4}$$

Letting M_b denote the total number of associated users at BS b, it is supposed that $1\leq\cdots\leq\gamma_{b,M_b-1}\leq\gamma_{b,M_b}$, and thus the SIC order is $M_b\rightarrow M_b-1\rightarrow\cdots\rightarrow 1$. Note that the binary decoding decision indicators, $\lambda_{b,k,m},\forall k,m\in\mathcal{M}_b$, are determined by SINR ordering. In addition, from [6], the optimal PACs for solving the sum-rate maximization are given in a closed form as

$$p_{b,m}^*=\left[\beta\left((1-\beta)^{m-1}a_bP_b^{max}+\frac{1}{\tilde{h}_{b,i}}-\sum_{j=1}^{m-1}\frac{\beta(1-\beta)^{m-j-1}}{\tilde{h}_{b,j}}\right)\right]^+,\forall m=1,\ldots,M_b-1, \tag{5}$$

$$p_{b,M_b}^{\Delta}=\left[a_bP_b^{max}-\sum_{m=1}^{M_b-1}p_{b,m}^*\right]^+, \tag{6}$$

where $\beta=\frac{2^{R_{min}}-1}{2^{R_{min}}}$, $\tilde{h}_{b,m}=\frac{h_{b,m}}{I_{b,m}+\sigma^2}$, and $[\cdot]^+=\max\{0,\cdot\}$. In (6), the PAC for user M_b is the remaining power after the PACs for users $1,\ldots,M_b-1$ are determined by (5) to achieve the minimum SE requirement, because allocating more power to the user with the best SINR, γ_{b,M_b}, can maximize the total SE.

After that, we can consider the PACs for all users (including user M_b) in a cell to guarantee the minimum SE requirement. Thus, the PAC of user M_b is obtained by using (5), instead of (6). Then, the sum of the PACs in (5) can be expressed as

$$\sum_{m=1}^{M_b}p_{b,m}^*=a_bP_b^{max}(1-(1-\beta)^{M_b})+\sum_{m=1}^{M_b}\frac{\beta}{\tilde{h}_{b,m}}(1-\beta)^{M_b-m}, \tag{7}$$

where the sum of the PACs should meet the power constraint such that $\sum_{i=1}^{M_b}p_{b,m}^*\leq a_bP_b^{max}$. Hence, we can obtain the following condition:

$$\sum_{i=1}^{M_b}\frac{\beta}{\tilde{h}_{b,m}}(1-\beta)^{-m}\leq a_bP_b^{max}. \tag{8}$$

Moreover, according to the optimal PACs in (5) and (6), the objective for SE maximization in (2a) can be equivalently transformed to $\sum_{b\in\mathcal{B}}(\sum_{m\in\mathcal{M}_b\backslash\{M_b\}}R_{min}+\log_2(1+p_{b,M_b}^{\Delta}\tilde{h}_{b,M_b}))$. Then, (2) can be transformed as follows:

$$\max_{\forall a_b}\sum_{b\in\mathcal{B}}\log_2(1+p_{b,M_b}^{\Delta}\tilde{h}_{b,M_b}), \tag{9a}$$

$$\text{s.t.}\quad 0\leq a_b\leq 1,\qquad \forall b\in\mathcal{B}, \tag{9b}$$

$$\sum_{m=1}^{M_b}\frac{\beta}{\tilde{h}_{b,m}}(1-\beta)^{-m}\leq a_bP_b^{max},\qquad \forall b\in\mathcal{B}. \tag{9c}$$

Furthermore, using (7), (6) can be formulated to $(1-\beta)^{M_b-1}(a_bP_b^{max}-\sum_{m=1}^{M_b-1}\frac{\beta}{\tilde{h}_{b,m}}(1-\beta)^{-m})$. Then, we can rewrite the constraint in (9c) as

$$\sum_{m=1}^{M_b} \frac{\beta}{\tilde{h}_{b,m}}(1-\beta)^{-m} \le a_b P_b^{max}$$
$$\Longrightarrow p_{b,M_b}^{\Delta} \tilde{h}_{b,M_b} \ge \frac{\beta}{1-\beta} \tag{10}$$
$$\Longrightarrow \log_2(1+p_{b,M_b}^{\Delta}\tilde{h}_{b,M_b}) - \log_2\left(\frac{1}{1-\beta}\right) \ge 0.$$

Therefore, since $\log_2(\frac{1}{1-\beta})$ in (10) is a constant, we can prove that the constraint in (9c) can be equivalently transformed to the objective function in (9a). In addition, (9c) can be converted to $\sum_{m\in\mathcal{M}_b} \frac{\beta}{\gamma_{b,m}(1-\beta)^m} \le 1$. Then, using (4) and (10), the JSPA optimization problem in (2) can be converted as follows:

$$\min_{\forall a_b} \sum_{b\in\mathcal{B}} \sum_{m\in\mathcal{M}_b} \frac{\beta}{\gamma_{b,m}(1-\beta)^m}, \tag{11a}$$
$$\text{s.t.} \quad 0 \le a_b \le 1, \qquad \forall b \in \mathcal{B}, \tag{11b}$$
$$\sum_{m\in\mathcal{M}_b} \frac{\beta}{\gamma_{b,m}(1-\beta)^m} \le 1, \qquad \forall b \in \mathcal{B}. \tag{11c}$$

Using the simplified optimization problem in (11), we present the DNN-based JSPA algorithm which is entirely different from the conventional unsupervised learning approaches in [3,7]. In Fig. 2, the proposed DNN-based processes are presented, where the first process is the normalization for channel gain with the logarithm scale, which is expressed as

$$\hat{h}_{b,u} = \log_{10}\left(1 + \frac{h_{b,u}P_b^{max}}{\sigma^2}\right), \forall b \in \mathcal{B}, \forall u \in \mathcal{U}, \tag{12}$$

where the normalization process is typically used to facilitate the DNN-based optimization. After the normalization process, the normalized channel state information (CSI) data in (12) is fed into the DNN structure, which consists of fully connected (FC) layers while each layer is regularized by rectified linear unit (ReLU). It is noted that the DNN structure is configured by two hidden layers, and the number of hidden nodes is denoted by S. Letting the trainable weight matrix and bias vector be denoted as $\boldsymbol{W}$ and $\boldsymbol{c}$, respectively, the FC layer conducts the following operation, $f(\boldsymbol{x}) = \boldsymbol{W}\boldsymbol{x} + \boldsymbol{c}$. Moreover, in each layer, the batch normalization and dropout processes are conducted to prevent overfitting and to speed up the optimization process. The structure of the considered DNN is illustrated in Table 1, where the hidden layer type, size, depth, and normalization methods have been chosen through exhaustive experiments, and they will be introduced in Section 4. Then, the output layer is reduced to B, and it becomes the input of the sigmoid function, where the sigmoid function can regularize its output from 0 to 1, and it satisfies the constraint of PCCs in (11b). Let $\boldsymbol{\Xi}$ be defined as the output vector of the second hidden layer in Table 1. Then, the proposed DNN-based PCC is obtained as

$$a_b^{DNN} = \frac{1}{1+e^{-\Xi_b}}, \forall b \in \mathcal{B}, \tag{13}$$

where Ξ_b is the bth element of vector $\boldsymbol{\Xi}$. Additionally, it is noted that the proposed PCC in (13) can keep the constraint in (11b) due to the characteristic of the sigmoid function.

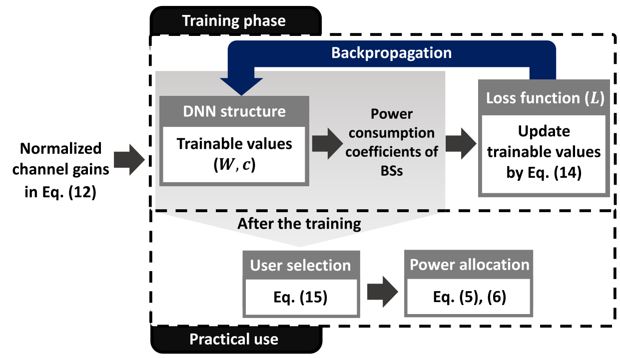

Fig. 2. Proposed training and practical use mechanism.

Table 1
Description of proposed DNN architecture.

Layer	Size	Network structure	
Input	BU	–	
1st hidden layer	$S = 1000$	Type	Fully connected Batch normalization Dropout
		Activation	ReLU
2nd hidden layer	$S = 1000$	Type	Fully connected Batch normalization Dropout
		Activation	ReLU
Output	B	Activation	Sigmoid

Then, considering optimization problem in (11), we define a new loss function as

$$L = \sum_{b\in\mathcal{B}} \sum_{m\in\mathcal{M}_b} \frac{\beta}{\gamma_{b,m}(1-\beta)^m}. \tag{14}$$

Based on the loss function in (14), the trainable weight and bias values of the DNN structure in Fig. 2, $\boldsymbol{W}$ and $\boldsymbol{c}$, are updated by the backpropagation procedure to train the PCCs in (13) for solving the optimization problem in (11). The weight matrix and the bias vector are updated by $W_t = W_{t-1} - \eta\frac{\partial L_t}{\partial W_{t-1}}$ and $c_t = c_{t-1} - \eta\frac{\partial L_t}{\partial c_{t-1}}$, respectively, where W_t, c_t, and L_t represent the weight matrix, the bias vector, and the loss function at learning time t, respectively, and η is the learning rate. Additionally, following some training iterations, the proposed loss function is regularized within the range of $0 \le L \le B$ due to the constraint in (11c). The regularization of the loss function can enhance training performance compared with the loss functions used in previous studies [3,7]. During the training, it is noted that the binary decision indicator, $\lambda_{b,m,k}, \forall b \in \mathcal{B}, \forall m, k \in \mathcal{M}_b$, and the corresponding user set, $\Phi_{b,m}, \forall b \in \mathcal{B}, \forall m, k \in \mathcal{M}_b$, are varied by the updated PCCs. Accordingly, it is demonstrated that the proposed loss function can obviously optimize the considered JSPA problem, which is definitely different from the conventional DNN-based training algorithm.

3.2. Practical use of DNN-based JSPA with user selection

After the training process based on the loss function in (14), the trained DNN structure can provide the appropriate PCCs for solving the optimization problem in (11) without any iterations. However, the closed-form expressions for the PACs in (5) and (6) are not optimal when an outage event occurs, i.e., any user cannot achieve the minimum SE requirement in (2b). Accordingly, as in the practical use of Fig. 2, before the PA, we introduce a user selection algorithm to exclude users who cannot meet the minimum SE requirement.

For user selection, we use (11c), which is the constraint for satisfying the minimum SE requirement. From the SINR order, $\gamma_{b,1} \leq \gamma_{b,2} \leq \cdots \leq \gamma_{b,M_b}$, the priority of user selection follows the order of $M_b \to \cdots \to 2 \to 1$ in the user selection algorithm. First, let us consider a single-user case. Then, we can derive the condition to select the user as $\frac{\beta}{\gamma_{b,1}(1-\beta)} \leq 1$. Since $\gamma_{b,1}$ is always positive, it is rewritten as $\gamma_{b,1} \geq \frac{\beta}{1-\beta}$. Thus, for a single-user case, the user satisfies the SE requirement when this inequality holds. Similarly, for two users, the condition to select the two users is given as $\frac{\beta}{\gamma_{b,1}(1-\beta)} + \frac{\beta}{\gamma_{b,2}(1-\beta)^2} \leq 1$, which can be rewritten as $\gamma_{b,1} \geq \beta / \left[1-\beta-\frac{\beta}{\gamma_{b,2}(1-\beta)}\right]^+$. If this is not satisfied, user 1 is excluded by user selection, and the condition $\gamma_{b,1} \geq \frac{\beta}{1-\beta}$ is recalled to select user 2. Thus, the user selection conditions can be generalized for M_b users as

$$\gamma_{b,m} \geq \frac{\beta}{\left[1-\beta-\sum_{k=m+1}^{M_b} \frac{\beta}{\gamma_{b,k}(1-\beta)^{k-m}}\right]^+}, \forall b \in \mathcal{B}, \forall m \in \mathcal{M}_b. \tag{15}$$

According to the proposed user selection algorithm, the only users that can satisfy (15) successfully have the PACs in (5) and (6). It is noted that the proposed algorithm can obtain the optimal PACs in closed form, unlike the algorithm in [6], because of the user selection process. Moreover, the proposed algorithm can achieve better performance and lower complexity than the conventional user selection schemes in [9, 10].

4. Simulation results

In this section, we provide the extensive simulation results of the total SE and outage rate for the performance evaluation of our proposed scheme. In addition, we assume the simulation parameters and their values in Table 2. Moreover, for performance comparison, we consider the following schemes:

- **Proposed DNN-based JSPU** : The JSPA with user selection (JSPU) scheme is described in Section 3.
- **Proposed DNN-based JSPA** : The JSPA is described in Section 3.1, which does not include the user selection process in 3.2.
- **DNN-based PA** : Based on the training algorithms in [3, 7], the PCC and PACs are jointly allocated by DNN. It is noted that the DNN-based PA requires two DNN structures for deriving the PCCs and PACs, respectively.

Table 2
Simulation parameters and hyperparameters.

Parameters	Values
Number of macro and BSs (B)	4
Radius of macro cell	500 [m]
Location of macro BS	(0 m, 0°)
Locations of small BSs	(250 m, 0°), (250 m, 120°), (250 m, 240°)
Number of users (U)	10–30
Maximum powers of macro and small BSs (P_b^{max})	30 [dBm]/27 [dBm]
Path loss coefficient (α)	4.0
Noise power (σ^2)	−114 [dBm]
QoS requirement (R_{min})	0.1–0.5 [bps/Hz]
Number of training data samples	300,000
Number of testing data samples	10,000
Number of hidden nodes (S)	1,000
Batch size	10,000
Learning rate (η)	0.0001
Dropout rate	0.2
Optimizer	Adam optimizer

Table 3
Computational complexity of algorithms.

Algorithm	Complexity
Proposed DNN-based JSPU	$\mathcal{O}(BUS+S^2+BS)$
Proposed DNN-based JSPA	$\mathcal{O}(BUS+S^2+BS)$
DNN-based PA	$\mathcal{O}(2(BUS+S^2)+BS+BUS)$
Decentralized JSPA	$\mathcal{O}(1)$
Optimal JSPU	$\mathcal{O}(K^B)$

- **Decentralized JSPA** : In this scheme, the PACs are obtained by (5) and (6) in a distributed manner, which is presented in [6]. For this scheme, we assume $a_b = 1, \forall b \in \mathcal{B}$, i.e., all the BSs utilize the maximum transmit power.
- **Optimal JSPU** : The optimal achievable power is found by the JSPA algorithm in [6] with the user selection algorithm in Section 3.2. The samples of the PCC, $a_b, \forall b \in \mathcal{B}$, are collected with an equal step size, where the total number of samples is $K = 100$ for simulations. The optimal PCCs from the samples are determined by an exhaustive search in a centralized manner.

The complexities of the five schemes are presented in Table 3, where the complexity of the DNN-based schemes is derived based on the floating-point operations (FLOPs) [3,8]. On the other hand, the complexity of decentralized JSPA and optimal JSPU algorithms is presented in [6]. From Table 3, it is verified that the proposed DNN-based JSPU has a considerably low complexity as compared to the optimal JSPU scheme that requires exponential complexity.

Figs. 3 and 4 show the impact of the QoS requirement, R_{min}, on the SE and outage performances, respectively. In

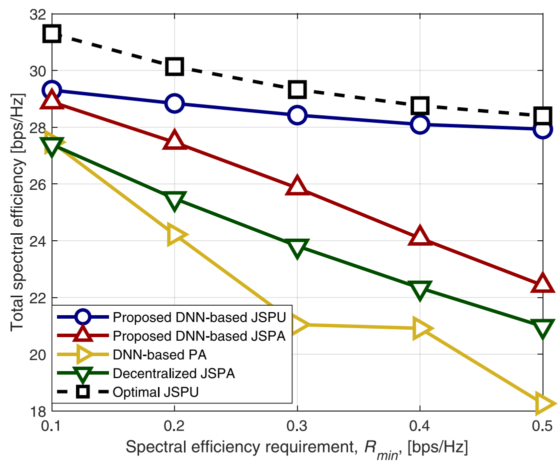

Fig. 3. Total SE versus R_{min}, when $U = 10$ and $B = 4$.

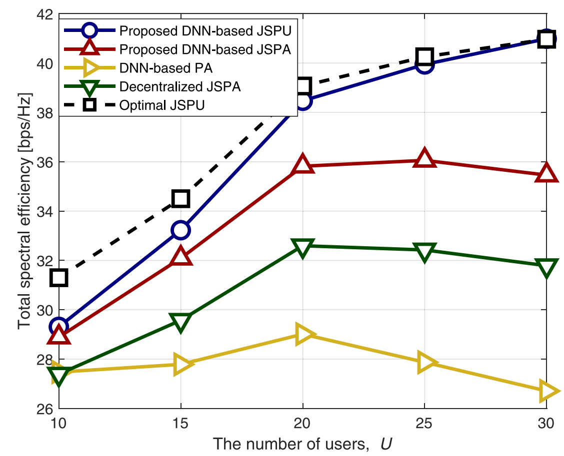

Fig. 5. Total SE versus U, when $R_{min} = 0.1$ and $B = 4$..

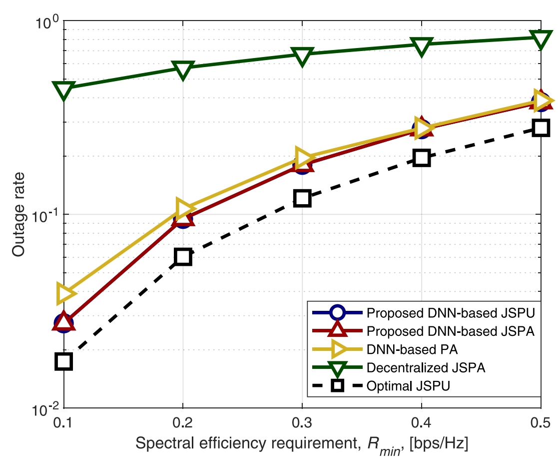

Fig. 4. Outage rate versus R_{min}, when $U = 10$ and $B = 4$..

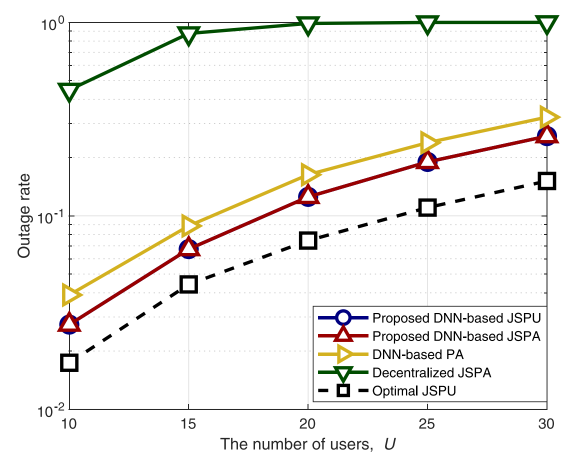

Fig. 6. Outage rate versus U, when $R_{min} = 0.1$ and $B = 4$..

Fig. 3, the proposed DNN-based JSPU attains a comparable SE result with the optimal JSPU for high R_{min}, and it provides the best SE result among the three DNN-based schemes. Fig. 4 illustrates that the proposed DNN-based JSPU has worse outage rates compared with the optimal JSPU, but it achieves the best outage performance among the other schemes except the optimal JSPU. Especially, when comparing the proposed DNN-based JSPU and JSPA in Figs. 3 and 4, the proposed user selection scheme attains considerably higher SE while maintaining the outage performance. In addition, the DNN-based PA brings out the lowest total SE for all R_{min} even when it has a higher outage rate compared with the proposed DNN-based schemes. From these results, it seems that the proposed training algorithm can enhance both SE and outage performances than the conventional DNN-based PA algorithm. Moreover, the decentralized JSPA scheme has the worst outage rate compared with the other schemes, because it cannot manage the inter-cell interference.

Figs. 5 and 6 show the impact of U on the SE and outage performances, respectively. From these figures, it is observed that the SE result of the proposed DNN-based JSPU becomes closer to that of the optimal JSPU as U increases, but it has a worse outage performance than the optimal one. Also, the SE results of the schemes without user selection (i.e., proposed DNN-based JSPA, DNN-based PA, and decentralized JSPA) are degraded as U increases from 20, whereas the SE results of the two JSPU schemes using user selection always increase with U. It is noted that the proposed user selection can effectively enhance the SE in a massive user environment.

5. Conclusion

In this paper, we address the low-complexity algorithm for JSPA using DL in the NOMA-enabled HetNet for maximizing the total SE under the QoS requirement. However, since the JSPA problem is regarded as a MINLP problem, we newly present the simplified problem which optimizes only the PCC of BSs. Using the presented problem, we propose the DNN-based training algorithm based on the unsupervised learning approach to enhance the training performance compared with the conventional unsupervised schemes. In addition, we employ the user selection algorithm to enhance the SE performance with low complexity. Through performance evaluation, we provide that the proposed DNN-based JSPA with user selection can achieve comparable SE and outage performances to the optimal scheme, while significantly reducing the computational complexity. Moreover, it provides outstanding performance than the conventional DNN-based approach. Therefore, the proposed scheme can be considered as an effective solution to enhance the SE with low complexity in the downlink NOMA-based HetNet.

CRediT authorship contribution statement

Donghyeon Kim: Writing – original draft, Conceptualization. **Jung-Bin Kim:** Writing – review & editing, Project administration, Investigation. **Haejoon Jung:** Writing – review & editing, Investigation. **In-Ho Lee:** Writing – review & editing, Supervision.

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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