Deep Learning-based Power Allocation in Massive MIMO Systems with SLNR and SINR Criterions

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***Abstract*—In this paper, we design a deep learning framework for the power allocation problems in massive MIMO networks. In particular, we formulate the max-min and max-product power allocation problems by using signal-to-interference-plus-noise ratio (SINR) and signal-to-leak-plus-noise ratio (SLNR) criteria for linear precoder design. Multiple base stations are deployed to serve multiple user equipments, the power allocation process to each user equipment takes long processing time to converge, which is inefficient approach. We tackle this problem by designing a framework based on deep neural network, where the user equipment position is used to train the deep model, and then it is used to predict the optimal power allocation according to the user's locations. The resulting deep learning helps to reduce the processing time of the system in determining the optimal power allocation for the user equipment. Compared to the standard optimization approach, the deep learning design helps to obtain the optimal solution of the power allocation problem within a short time via a quick-inference process. Simulation results show that the SINR criterion outperforms the SLNR one. Meanwhile, deep learning performance in predicting power allocation gets excellent results with an accuracy of 85% for the max-min strategy and 99% for the max-product strategy.**

***Index Terms*—Deep neural networks, massive MIMO, power allocation, signal-to-leak-plus-noise ratio (SLNR), signal-to-interference-plus-noise ratio (SINR).**

I. Introduction

In massive multiple-input multiple-output (MIMO), the base station (BS) with large antenna arrays (hundreds of antennas) can serve many users simultaneously [1]. Massive MIMO has been emerged as an advanced wireless network technology to provide high spectral and energy efficiencies. Thus, deploying a larger number of antennas will increase the throughputs for the uplink and downlink in a dynamic wireless propagation environment. However, the author in [1] only discussed the effect of changing the number of antennas on the throughput value. The author in [2] focused on improving the spectral efficiency by using join spatial division and reuse (JSDR) carrier sensing schemes to improve the spectral efficiency (SE) by considering multiplexed signaling. However, the paper did not consider the efficiency of transmit power allocation. In massive MIMO systems, the transmit power can be allocated in a small area to offer large improvements of throughput and energy efficiency [3]. The author in [4] worked on hybrid user pairing (HUP) for spectral and energy efficiency for multiuser multiple-input single-ouput (MISO) nonorthogonal multiple access (NOMA) downlink systems with simultaneous wireless information and power transfer (SWIPT). However, the author only focused on the problem of user pairing by using conventional methods, which took a long processing time to obtain the optimal power allocation solution.

Deep learning (DL) has been applied in wireless communications to solve many problems such as prediction of power allocation with signal-to-interference-plus-noise ratio (SINR) criterion [5]. In [6], DL was used for channel estimation in MIMO systems with signal-to-noise ratio (SNR). Moreover, in [7], deep learning was used to determine link scheduling based on the positions of the transmitter and receiver. The author in [8] focused on the deep neural network (DNN) to predict the secrecy performance on physical layer security. The author in [9] studied DNN based relay selection scheme to evaluate and improve the end-to-end throughput in wireless-powered cognitive Internet-of-Things (IoT) networks. Nevertheless, it does not discuss power allocation. The author in [10] concentrated on deep learning evaluation of short-packet communication in wireless-powered cognitive IoT network. DL demonstrates the ability to study historical data and generates patterns to predict results with unprecedented input data [7]–[12].

In this paper, we design deep learning (DL) framework for the precoder design in downlink massive MIMO networks. In general, the minimum leakage, indicated by signal-to-leakage-plus-noise ratio (SLNR), and maximum per-stream, indicated by signal-to-interference-plus-noise ratio (SINR), are two essential criteria for precoder design in MIMO systems [13]. In SINR, BS chooses user equipment (UE) with estimated SINR one by one; on the other hand, in SLNR, BS chooses the user with the largest SLNR. Due to a large number of BSs and UEs, allocating power to user equipment at the BS renders a complex problem, which is difficult to solve efficiently. The main contributions of the paper can be summarized as follows:

- We propose two criteria, namely, SINR and SLNR, to solve max-min and max-product power allocation problems in massive MIMO systems.
- We design a DL framework to achieve the optimal solution of the power allocation for the considered system setup based on the position information of UE. The DL approach aims to reduce the complexity in determining the power allocation to UE. Thus, determining the power allocation can be done in real-time with the position of

the user equipment moving around.

- Simulation results will be compared with conventional methods to show the performance of the deep neural network design. The performance of the proposed DNN has good results with an accuracy of 85% to 99%.

Notation: Matrices are denoted by bold-face, upper-case letters ($\mathbf{R}$), vectors are bold-face, lower-case letters ($\mathbf{w}$), and scalars with lower-case letters (x). $\mathcal{N}_{\mathbb{C}}(\mathbf{0}, \mathbf{I})$ is circularly symmetric complex Gaussian distribution with zero mean and correlation matrix $\mathbf{I}$. $\|.\|$ stands is the vector's Euclidean norm. The complex numbers denote as $\mathbb{C}$, and $\mathbf{I}_M$ is $M \times M$ identity matrix.

II. System Model

We consider a downlink multiuser multicell massive MIMO system, where a BS with M antennas in each cell l is deployed to serve K UEs shown in Fig. 1. The SINR and SLNR approaches are used to determine the max product SINR and max product SLNR strategies. SLNR is employed to reflect a user's leakage capacity to all other users [13]. Higher SLNR indicates greater channel gain and lower leakage capacity [14]. It is worth noting that a user's leakage power is simply an intrusion from other users' perspectives. Consequently, when all UE have low leakage energy, which means that each UE has minimal interference energy from others. Besides, the benefit of SINR is that a higher SINR directly translates to a higher rate. The calculation of SINR, on the other hand, requires all other users', which is challenging to know precisely.

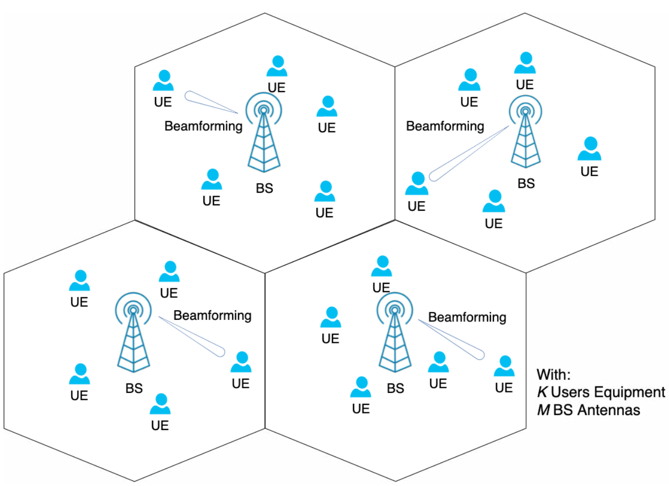

Fig. 1. The proposed multiuser multicell massive MIMO systems.

The received signal for user i in cell l can be expressed as

$$y_{li} = \mathbf{h}_{li}\mathbf{w}_{li}\varsigma_{li} + \sum_{i=1, i\neq 1}^{K} \mathbf{h}_{li}\mathbf{w}_{li}\varsigma_{li} + n_{li}, \quad (1)$$

where $\mathbf{h}_i$ is the user's channel vector i, $n_{li} \sim N_{\mathbb{C}}(0, \rho_{li})$ is additive white Gaussian noise, $\mathbf{w}_{li}$ is the unit-norm beamforming vector for user i in cell l, and ς_{li} is the DL data signal for user i in cell l. The SNR per-user can be described as $1/\sigma_i^2$. The SINR is defined as

$$\text{SINR}_{li} = \frac{\|\mathbf{h}_i \mathbf{w}_i\|^2}{\sum_{k=1, k\neq i}^{N} \|\mathbf{h}_i \mathbf{w}_k\|^2 + \sigma^2}. \quad (2)$$

The calculation of SINR requires the information of all users' $\mathbf{w}_k$, which is challenging to know precisely. On the other hand, the SLNR of the user i in cell l is defined as

$$\text{SLNR}_{li} = \frac{\|\mathbf{h}_i \mathbf{w}_i\|^2}{\sum_{k=1, k\neq i}^{N} \|\mathbf{h}_k \mathbf{w}_i\|^2 + \sigma^2}. \quad (3)$$

The SLNR is referred to user i's leakage power to all other users. Larger channel gain and lower leakage power are associated with higher SLNR. As a result, all users have low leakage capacity, which means that each user is subjected to minimal interference from others. It is worth noting that a user's leakage power is simply the intrusion from other users' viewpoints. As compared to the SINR_i, the measurement of SLNR_i does not include other users' beamforming vectors $\mathbf{w}_k$, $k \neq i$.

We denote the channel between UE i in cell l and BS j as $\mathbf{h}_{li}^j \in \mathbb{C}^M$, it can be expressed as

$$\mathbf{h}_{li}^j \sim \mathcal{N}_{\mathbb{C}}(\mathbf{0}_M, \mathbf{R}_{li}^j), \quad (4)$$

where $\mathbf{R}_{li}^j$ is the spatial correlation matrix known in BS, which is normalized by $\beta_{li}^j = 1/Mtr(\mathbf{R}_{li}^j)$. The average channel gain from antenna at BS j in cell l to UE i and can be modeled as

$$\beta_{li}^i = \gamma - 10\alpha log_{10}\left(\frac{d_{li}^j}{1km}\right) \text{dB}, \quad (5)$$

where the median channel gain at a 1km reference distance is determined by γ = -148 dB, and α = 3.76 is the coefficient of pathloss, d_{li}^j is the distance between UE i in cell l and BS j, $d_{li}^j = \|\mathbf{x}_{li}^j\|$ with $\mathbf{x}_{li}^j \in \mathbb{R}^2$ is the Euclidean space's UE position. It is worth noting that shadowing should be taken into account as well in (5). However, a log-normal distribution is usually used to model this, then resulting in a channel model that is not spatially consistent. In other words, two UEs nearby will not be uncovered to the same channel. To solve this problem, channel models based on ray tracing or recorded measurements should be used.

A. Channel Estimation

The channel vectors at BS j are estimated by using pilot-based channel preparation. We assume that the BS and UEs are perfectly synchronized. They follow a time-division duplex (TDD) protocol in which the DL data transmission process is followed in the UL by a channel estimation training phase. There are $\tau_p = K$ pilots (that is pilot reuse factor of 1) and the same pilot is used by UE i in every cell. Using the total UL pilot power of ρ^{tr} per UE, the standard estimation technique of minimum mean squared error (MMSE) with BS j obtains the estimates of $\hat{\mathbf{h}}_{li}^j$ as

$$\hat{\mathbf{h}}_{li}^j = \mathbf{R}_{li}^j \mathbf{Q}_{li}^{-1}\left(\sum_{l'=1}^{L} \mathbf{h}_{l'i}^j + \frac{1}{\tau_p}\frac{\sigma^2}{\rho}\mathbf{n}_{li}\right) \sim \mathcal{N}_{\mathbb{C}}\left(\mathbf{0}, \mathbf{\Phi}_{li}^j\right), \quad (6)$$

where $\mathbf{Q}_{li} = \sum_{l'=1}^{L} \mathbf{R}_{l'i}^{j} + \frac{1}{\rho^{tr}}\mathbf{I}_M$, $\mathbf{n}_{li} \sim \mathcal{N}_{\mathbb{C}}(\mathbf{0}, \mathbf{I}_M)$ is noise and $\Phi_{jli} = \mathbf{R}_{li}^{j}\mathbf{Q}_{li}^{-1}$. The estimator error is $\tilde{\mathbf{h}}_{li}^{j} = \mathbf{h}_{li}^{j} - \hat{\mathbf{h}}_{li}^{j} \sim \mathcal{N}_{\mathbb{C}}(\mathbf{0}, \mathbf{R}_{li}^{j} - \mathbf{\Phi}_{li}^{j})$ is indpendent of $\hat{\mathbf{h}}_{li}^{j}$.

B. Downlink Spectral Efficiency

The BS in cell l transmits the DL signal $\mathbf{x}_{li} = \sum_{i=1}^{K} \mathbf{w}_{li}\varsigma_{li}$ where $\varsigma_{li} \sim \mathcal{N}_{\mathbb{C}}(0, \rho_{li})$ is the DL data signal for UE i in cell l, allocated to a precoding vector $\mathbf{w}_{li} \in \mathbb{C}^{\mathbb{M}}$ that defines the transmission's spatial directivity and satisfies $\|\mathbf{w}_{li}\|^2 = 1$ so that ρ_{li} represents the transmit power.

In massive MIMO, the following hardening bound can be used to compute an achievable DL SE [15]. The DL ergodic channel capacity of UE i in cell l is lower bounded by

$$\mathsf{SE}_{li}^{\mathrm{dl}} = \frac{\tau_d}{\tau_c}\log_2(1 + \mathrm{SINR}_{li}^{\mathrm{dl}})[\mathrm{bit/s/Hz}], \tag{7}$$

or

$$\mathsf{SE}_{li}^{\mathrm{dl}} = \frac{\tau_d}{\tau_c}\log_2(1 + \mathrm{SLNR}_{li}^{\mathrm{dl}})[\mathrm{bit/s/Hz}], \tag{8}$$

where the standards are based on the channel's actualizations.

It is worth noting that the UE achieves the lower bound above by treating the mean of its precoded channel as the true one. For channels that show channel hardening, this is a rational assumption [16]. However, channels with little to no hardening suffer a loss.

C. Precoder Design

Unlike the UL described in [16], finding the optimal precoder is a challenge because DL SE in (2) and (3) relies on the $\{\mathbf{w}_{li}\}$ precoding vector of all UEs across the network. Based on the duality UL-DL [16], a suitable heuristic approach is to choose $\mathbf{w}_{jk}$ as

$$\mathbf{w}_{jk} = \frac{\mathbf{v}_{jk}}{\|\mathbf{v}_{jk}\|}, \tag{9}$$

where $\mathbf{w}_{jk}$ is predoding vector of UE k in cell j and $\mathbf{v}_{jk}$ is the combining vector for detecting the UL signal sent by UE k in cell j. In this paper, we assume that $\mathbf{v}_{jk}$ is built using maximum ratio (MR) combining,i.e.,

$$\mathbf{v}_{jk}^{\mathrm{MR}} = \hat{\mathbf{h}}_{jk}^{j}, \tag{10}$$

and multicell MMSE (M-MMSE) combining [17], [18]

$$\mathbf{v}_{jk}^{\text{M-MMSE}} = \left(\sum_{l=1}^{L}\sum_{i=1}^{K} \hat{\mathbf{h}}_{li}^{j}(\hat{\mathbf{h}}_{li}^{j})^{H} + \mathbf{Z}_j\right)^{-1} \hat{\mathbf{h}}_{jk}^{j}, \tag{11}$$

where

$$\mathbf{Z}j = \sum_{l=1}^{L}\sum_{i=1}^{K}\left(\mathbf{R}_{li}^{j} = \mathbf{\Phi}_{li}^{j}\right) + \frac{\phi_{ul}^{2}}{\rho_{ul}}\mathbf{I}_M. \tag{12}$$

Base on (11), the M-MMSE is optimal but has high computational complexity. On the other hand, MR is suboptimal (not just for M's finite values, but even for M is ∞), but it has the simplest complexity of combining schemes.

III. Power Allocation

The downlink (DL) spectral efficiency (SE) of user equipment (UE) *k* in cell *j*, written on (7) and (8), is averaged for small-scale fading realization, so the DL SE is just a function of the large-scale fading statistic initial coding preference. As compared to single antenna systems, this is a unique aspect of massive MIMO that significantly simplifies power allocation problems [16].

There are two famous examples among the various power allocation policies, namely the max-min fairness and max product strategies, which can be formulated as

$$\max_{\{\rho_{jk}:\forall j,k\}} \min_{j,k} \mathsf{SE}_{jk}^{\mathrm{dl}}, \tag{13}$$

subject to

$$\sum_{k=1}^{K} \rho_{jk} \leq P_{max}^{\mathrm{dl}}, j = 1, ..., L.$$

and

$$\max_{\{\rho_{jk}:\forall j,k\}} \prod_{j=1}^{L}\prod_{k=1}^{K} \mathrm{SINR}_{jk}^{\mathrm{dl}} \tag{14}$$

or

$$\max_{\{\rho_{jk}:\forall j,k\}} \prod_{j=1}^{L}\prod_{k=1}^{K} \mathrm{SLNR}_{jk}^{\mathrm{dl}} \tag{15}$$

subject to (13) for maximum production, where P_{max}^{dl} denotes the maximum DL transmit power. The following Monte Carlo technique is needed to compute the optimal powers, regardless of the power allocation strategy. To find the optimal solution in determining the power allocation is shown in the algorithm 1.

The (13) can be solved using a bisection technique, which involves solving a series of convex problems, while (14) and (15) can be solved using geometric programming. As a result, both (13),(14) and (15) must be solved with a polynomial or quasi-polynomial complexity. When the solution must be obtained in real-time, that is not quick enough to be implemented before the UEs' positions change, and the power allocation problem must be solved again because a polynomial complexity may increase significantly.

IV. Deep Neural Network Design

In this section, we develop a DL framework for power allocation in multicell massive MIMO systems. As shown in Fig. 2, the DNN approach is different from the conventional optimisation approaches which use (13), (14) and (15) requiring knowledge of channel state information $\{\mathbf{h}_i\mathbf{w}_i\}$ and $\{\mathbf{h}_i\mathbf{w}_k\}$ as well as $\{\mathbf{h}_k\mathbf{w}_i\}$ in (2) and (3), and take much time to obtain optimal solutions. In our proposed DL framework, the optimal solution of problem (13) will be obtained from solving by using algorithm 1 or conventional optimization method and the output will be used as the target of the DNN model. If the output or the optimal solution gets error, the DNN model will learn until the minimize error can be found.

Algorithm 1 Power Allocation Procedure for Solving Problem (13)

Input: SINR, SLNR, P_{max}, $\frac{\tau_d}{\tau_c}$
Output: Power optimum

Initialization :
Set rate lower =0, rate uppper = $\log_2$ (1+ $P_{max} \times$ min(SINR) or rate uppper = $\log_2$ (1+ $P_{max} \times$ min(SLNR), and accuracy (delta) = 0.01.

```
while rate upper - rate lower > delta do
    rate candidate = (rate lower + rate upper)/2
    for j=1 to 4 do
        for k=1 to K do
            if SINR(k,j) > 0 or SLNR(k,j) > 0 then
                Solve the problem (14) or (15)
                scaling = scaling < 0
            end if
        end for
    end for
    Scaling = Scaling > 0
    if solve then
        feasible = false
        SINR or SLNR solution = [ ]
    else if scaling > 1 then
        feasible = false
        SINR or SLNR solution = SINR or SLNR
    else
        feasible = true
        SINR or SLNR solution = SINR or SLNR
    end if
    if feasible then
        rate lower = rate candidate
        SINR best = SINR candidate, or SLNR best = SLNR candidate
    else
        rate upper = rate candidate
    end if
end while
Solve the problem (7) or (8) for the optimal solution power allocation
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The UE positions are used as the input of DNN input because they have the essential characteristics of propagation channels and network interference and the output is the optimal power allocation. The problem is to learn the unknown position between the solution to (13), (14) or (15) and the $2KL$ geographical UE positions $\mathbf{x} = \{\mathbf{x}_{li}^{j}; \forall j, l, i\} \in \mathbb{R}^{2KL}$ for any given cell j. This is accomplished by taking advantage of DNNs' well-known property of being universal function approximators [20], [11]. We use a feedforward neural network with a $2KL$-dimensional input layer, N hidden layers, and a K + 1-dimensional output layer to produce an approximation $\hat{\rho}_j = [\hat{\rho}_{j1}, ...\hat{\rho}_{jk}]$ of the optimal power allocation vector $\rho_j^{\star}$, as shown in Fig. 3. Since we also make the DNN learn $\sum_{k=1}^{K} \rho_{jk}^{\star}$ to fulfill the power constraint and improve the estimation accuracy, the output layer has size K+1. After doing feedforward, we will get an error or the difference between

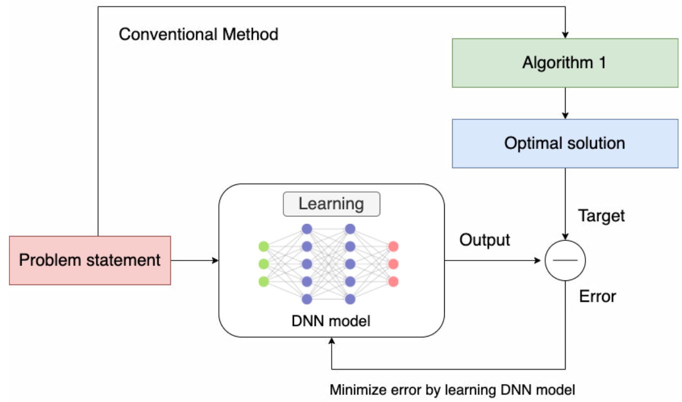

Fig. 2. The DNN-based approach to learn optimization via minimizing the error of solution between conventional algorithm and DNN model [19].

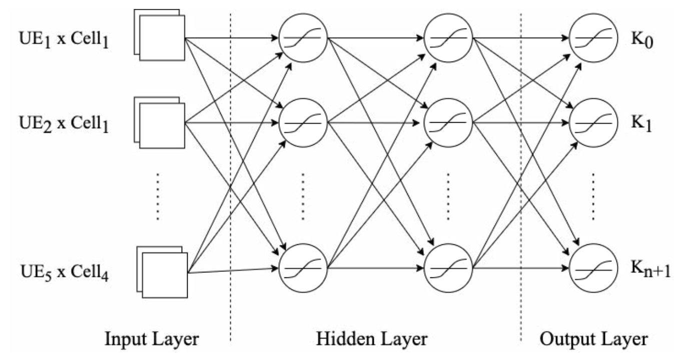

Fig. 3. The proposed DNN model for power allucation, where the rectified linear unit is used as the activation function in every hidden layer.

the output and the target. We will then update the weight using backpropagation, which is done continuously until the iteration is fulfilled [20]. The DNN will calculate the best

TABLE I
MODEL OF DEEP NEURAL NETWORK ON MAX-PRODUCT STRATEGY

	Size	Activation function
Input	40	-
Layer 1	512	ELU
Layer 2	512	ELU
Layer 3	256	ELU
Layer 4	128	ELU
Layer 5	12	ELU
Layer 6	6	LINEAR

power allocation strategy for inputs that are not in the training set. As a result, if the UEs' positions in the network change, the power allocation can be changed by simply feeding the new positions to the DNN, rather than solving (13), (14) or (15). Therefore, the proposed solution can significantly reduce complexity and allow for real-time power allocation based on UE positions. The layer structure of the deep learning design used for the max-product strategy is shown in Table I while that for the max-min strategy is shown in Table II.

TABLE II
MODEL OF DEEP LEARNING NEURAL NETWORK ON MAX-MIN STRATEGY

	Size	Activation function
Input	40	-
Layer 1	1024	ELU
Layer 2	1024	ELU
Layer 3	512	ELU
Layer 4	512	ELU
Layer 5	5	LINEAR

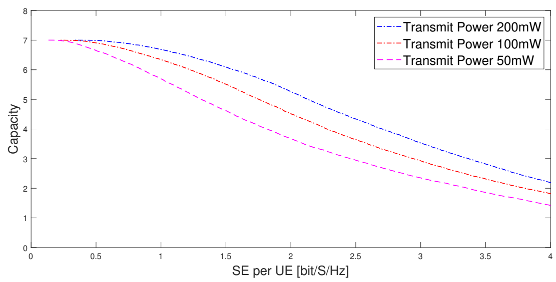

Fig. 4. Capacity of the Spectrum Efficiency by Transmit Power.

V. SIMULATION RESULTS

In this section, we present illustrative numerical examples for the achievable performance of the proposed deep learning approach. In particular, we set in the simulations the number of base stations L= 4, the number of antennas of each BS M=100, and the number of user equipments in each BS K=5. The transmit power is set as 50mW, 100mW, and 200mW. A system with a transmit power of 50mW has the smallest capacity, while a system obtains the largest capacity with a transmit power of 200mW. Besides that, as the spectral efficiency increases, the capacity will decrease, as shown in Fig. 4. We display the cumulative distribution function (CDF) of the DL SE per UE. The UE position is random and shadow fading relization to evaluate the output of the DNN-based power allocation. We consider MR and M-MMSE with two criteria. For the DNN, we generate 10k samples, where 90% of samples is used for training and the remainder is used for validation. And we regenerate 100 dataset for the test of the DNN. The results are shown in Fig. 5. It is shown that the results with M-MMSE precoding on two SINR and SLNR criteria show that the use of DNN is very good with an accuracy of up to 99%.

While the SINR criteria shows a better performance than the SLNR criteria, Fig. 6 shows that the use of employing MR precoding shows a low level of accuracy compared to M-MMSE. DNN and the conventional method not really match, but the results are still good. Figures 5 and 6 illustrate the CDF of spectral efficiency for each user equipment. M-MMSE precoding is computationally more complex compared to MR precoding. The explanation is that in MR, precoding only considers the allocation power based on the desired signal gain. At the same time, in M-MMSE, it is done by considering the signal strength that interferes because DNN gets input in the form of the position of each UE on the network so that the use of M-MMSE precoding can be used optimally.

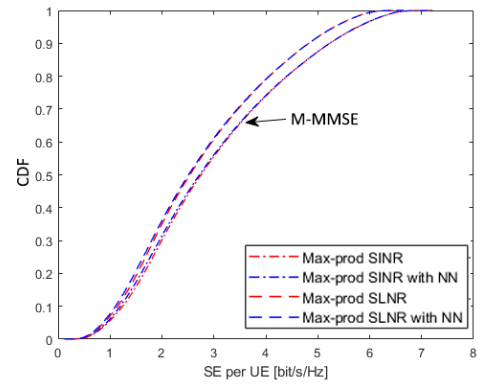

Fig. 5. CDF M-MMSE Precoding of the max product DL SE per UE.

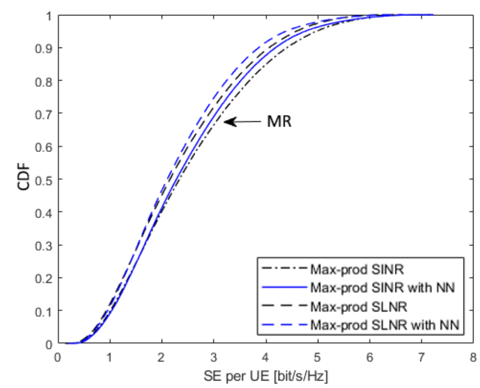

Fig. 6. CDF MR Precoding of the max product DL SE per UE.

The SINR is focused on a UE with interference from another UE, while SLNR is focused on how much power leakage rate there is in the UE, the SINR performance results are better than using SLNR selecting the user. The max-min strategy approach is shown in Fig. 7 and Fig. 8. The probability of displaying a result is almost the same as

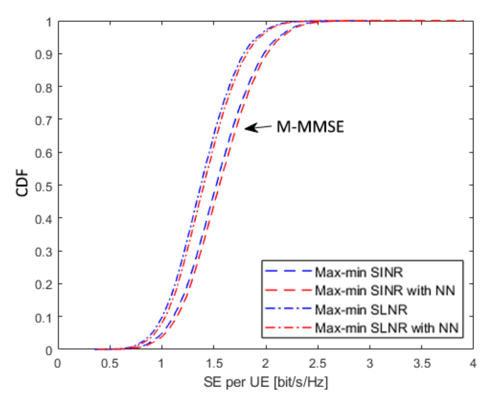

Fig. 7. CDF M-MMSE precoding of the max-min DL SE per UE.

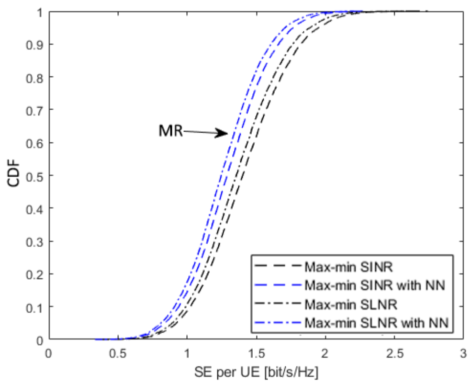

Fig. 8. CDF MR precoding of the max-min DL SE per UE.

for the max-product approximation. Performance from SINR shows better performance than SLNR. However, the use of M-MMSE precoding shown in Fig. 7 has better results than using MR precoding, shown in Fig. 8. The prediction results of DNN against conventional methods get not too promising results on MR precoding, which is only 85%. The process in the max-min policy has a higher difficulties than the max-product policy, so we need a more significant number of neural networks and training.

VI. Conclusions

This paper implemented deep learning with two-criterion approach (SINR and SLNR) to allocate downlink power in massive MIMO networks with MR and M-MMSE pre-codes. Analysis on massive MIMO behavior was performed with $L = 4$ cells and $K = 5$ UE per cell. The transmit power at 50mW was shown to have the smallest value since the increment of transmit power affected the received power in user equipment. Thus, each rise in transmit power will increase the channel capacity. On the other hand, the SE rate is inversely proportional to the channel capacity. Therefore, during the rise of SE rate, the bandwidth also increases, resulting in reduced channel capacity. Two strategies in power allocation were considered, namely max-min and max-product. We showed that the trained DNNs could learn how to allocate power to the UE in each cell with both strategies. Furthermore, relying solely on the UE's location in the network significantly reduced the optimization process's complexity and processing time. The simulation results showed that DNNs with SINR criteria using M-MMSE precode performed better than MR-based precode due to the nature of SINR that considered the allocation of received power with interference from other UE power—coupled with M-MMSE that allows DNNs to make the most available information. However, since the max-min policy is more difficult for DNNs to learn, more neural networks and extensive training parameters were required.

Acknowledgment

This work was supported by National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (NRF-2019R1A2C1083996).
Prof. Beongku An is the corresponding author.

References

[1] T. L. Marzetta, "Noncooperative Cellular Wireless with Unlimited Numbers of Base Station Antennas," *IEEE Trans. Wireless Commun.*, vol. 9, no. 11, pp. 3590–3600, 2010.

[2] J. Lee, K. J. Choi, and K. S. Kim, "Massive MIMO full-duplex for high-efficiency next generation WLAN systems," in *2016 Int. Conf. Inf. and Commun. Technol. Convergence (ICTC)*, Jeju, Korea (South), 2016, pp. 1152–1154.

[3] T. Le-Ngoc, "Keynote talk 1: 5G: From MIMO to massive MIMO," in *2016 3rd Nat. Found. for Sci. and Tech. Develop. Conf. Inf. and Comput. Sci. (NICS)*, Danang, Vietnam, 2016, pp. xviii–xix.

[4] T.-V. Nguyen, V.-D. Nguyen, D. B. da Costa, and B. An, "Hybrid User Pairing for Spectral and Energy Efficiencies in Multiuser MISO-NOMA Networks With SWIPT," *IEEE Trans. Wireless Commun.*, vol. 68, no. 8, pp. 4874–4890, 2020.

[5] L. Sanguinetti, A. Zappone, and M. Debbah, "Deep Learning Power Allocation in Massive MIMO," in *2018 52nd Asilomar Conf. on Signals, Syst., and Comput.*, Pacific Grove, CA, USA, 2018, pp. 1257–1261.

[6] J.-M. Kang, C.-J. Chun, and I.-M. Kim, "Deep Learning Based Channel Estimation for MIMO Systems With Received SNR Feedback," *IEEE Access*, vol. 8, pp. 121 162–121 181, 2020.

[7] W. Cui, K. Shen, and W. Yu, "Spatial Deep Learning for Wireless Scheduling," *IEEE J. Sel. Areas Commun.*, vol. 37, no. 6, pp. 1248–1261, 2019.

[8] K. Shim, T. N. Do, T.-V. Nguyen, D. B. da Costa, and B. An, "Enhancing PHY-Security of FD-Enabled NOMA Systems Using Jamming and User Selection: Performance Analysis and DNN Evaluation," *IEEE Internet Things J.*, pp. 1–1, 2021.

[9] T.-V. Nguyen, T.-N. Tran, K. Shim, T. Huynh-The, and B. An, "A Deep-Neural-Network-Based Relay Selection Scheme in Wireless-Powered Cognitive IoT Networks," *IEEE Internet Things J.*, vol. 8, no. 9, pp. 7423–7436, 2021.

[10] C. D. Ho, T.-V. Nguyen, T. Huynh-The, T.-T. Nguyen, D. B. da Costa, and B. An, "Short-Packet Communications in Wireless-Powered Cognitive IoT Networks: Performance Analysis and Deep Learning Evaluation," *IEEE Trans. Veh. Technol.*, vol. 70, no. 3, pp. 2894–2899, 2021.

[11] R. H. Y. Perdana and F. Fibriana, "An intelligent switch with back-propagation neural network based hybrid power system," *Journal of Physics: Conference Series*, vol. 983, p. 012056, mar 2018.

[12] H. Sun, X. Chen, Q. Shi, M. Hong, X. Fu, and N. D. Sidiropoulos, "Learning to Optimize: Training Deep Neural Networks for Interference Management," *IEEE Trans. Signal Process*, vol. 66, no. 20, pp. 5438–5453, 2018.

[13] A. E. Rakhmania, P.-Y. Tsai, and O. Setyawati, "Combined per-user SLNR and SINR criterions for interference alignment in uplink coordinated multi-point joint reception," in *Signal and Inf. Process Assoc. Annu. Summit and Conf. (APSIPA), 2014 Asia-Pacific*, Siem Reap, Cambodia, 2014, pp. 1–5.

[14] X. Xia, G. Wu, S. Fang, and S. Li, "SINR or SLNR: In Successive User Scheduling in MU-MIMO Broadcast Channel with Finite Rate Feedback," in *2010 Int. Conf. Commun. and Mobile Comput.*, vol. 2, Shenzhen, China, 2010, pp. 383–387.

[15] H. Y. Thomas L. Marzetta, Erik G. Larsson and H. Q. Ngo, *Fundamentals of Massive MIMO*. Cambridge University Press, 2016.

[16] Björnson, Emil and Hoydis, Jakob and Sanguinetti, Luca, *Massive MIMO Networks: Spectral, Energy, and Hardware Efficiency*, 2017.

[17] E. Björnson, J. Hoydis, and L. Sanguinetti, "Massive MIMO Has Unlimited Capacity," *IEEE Trans. Wireless Commun.*, vol. 17, no. 1, pp. 574–590, 2018.

[18] S. Mandal and S. Gauni, "Energy efficiency of single cell and multi cell Massive MIMO system MMSE estimation," in *2017 Int. Conf. Nextgen Electron. Technologies: Silicon to Softw. (ICNETS2)*, Chennai, India, 2017, pp. 66–70.

[19] M.-H. T. Nguyen, E. Garcia-Palacios, T. Do-Duy, L. D. Nguyen, S. T. Mai, and T. Q. Duong, "Spectrum-Sharing UAV-Assisted Mission-Critical Communication: Learning-Aided Real-Time Optimisation," *IEEE Access*, vol. 9, pp. 11 622–11 632, 2021.

[20] A. Zhang, Z. C. Lipton, M. Li, and A. J. Smola, *Dive into Deep Learning*, 2020, https://d2l.ai.