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A Joint Deep Learning and Genetic Algorithm Approach

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***Abstract*—Due to the limited number of radio frequency (RF) chains in millimeter wave (mmWave) massive multiple-input multiple-output (MIMO) receivers using analog beamforming/hybrid beamforming, there is a restriction in scheduling the number of users in each transmission time interval. Therefore, fast and low-complexity user scheduling methods based on the instantaneous channel state information (CSI) are needed. In this paper, we propose novel user scheduling methods based on deep learning (DL) to reduce the size of the search space by using the learning capability of a deep neural network (DNN). We formulate the user scheduling combinatorial optimization problem as a regression problem followed by a user separation procedure through decision boundaries that are learned by a trained DNN. The decision boundaries are used to separate the users into two subsets. Then, one of the subsets is selected to be searched to find the users that maximize the sum-rate capacity. The proposed method can achieve a very low outage probability with a few number of searches. In order to achieve ergodic capacity with lower computation complexity, the proposed method is employed in combination with the genetic algorithm (GA) algorithm to take advantage of intelligent initial population selection. Our simulation results show that the proposed user scheduling methods can offer remarkably low complexity.**

***Index Terms*—User scheduling, massive MIMO communications, hybrid beamforming, deep learning, Genetic algorithm.**

I. Introduction

Beamforming is a signal processing technique that enables the base stations (BSs) to transmit beams of data to increase the signal power for the intended users and minimize the interference for the non-intended users. Beamforming is considered a promising solution to improve the spectral efficiency and throughput of enhanced mobile broadband (eMBB) communications in the fifth-generation (5G) wireless systems [1]. In particular, massive multiple-input multiple-output (MIMO) systems in 5G mainly rely on beamforming techniques to simultaneously support a large number of users and reduce the effects of both path loss and interference, especially in millimeter wave (mmWave) bands [2], [3].

Since interference is the primary source of performance degradation in multi-user MIMO communications, an intelligent multi-user scheduling scheme is required to achieve high multiplexing gains. User scheduling enhances multi-user gain by selecting an optimal set of users that maximize the system utility [4]. The system utility can be the signal-to-interference-plus-noise ratio (SINR), spectral efficiency, or throughput.

Over the last decade, different antenna selection techniques in conjunction with fourth-generation (4G) multi-user MIMO communications have been developed to improve the spectral efficiency of the MIMO systems, where BS typically employs only a few (i.e., less than 10) antennas. With the advent of massive MIMO, user scheduling has been considered an attractive solution for 5G systems, where a subset of users are selected based on some criteria for downlink or uplink transmission [5]. Beam scheduling is formulated as a combinatorial optimization, where its objective is to find the optimal solution within a finite set of possible solutions. The set of possible solutions is defined by a set of constraints that is too large for an exhaustive search.

Deep learning (DL) has recently been considered a promising solution to solve combinatorial optimization problems. In [6], the authors showed that using DL in combination with the current combinatorial optimization algorithms can reduce the computational complexity. Motivated by the capabilities of DL, in this paper, we develop new user scheduling methods by using a deep neural network (DNN). Our DL-based methods can significantly reduce the computational complexity of the existing search algorithms and provide an approximate solution for the user scheduling combinatorial optimization problem. We formulate the user scheduling problem as a regression problem followed by a beam separation procedure. Using the trained DNN, we develop three fast and low-complexity beam scheduling methods.

A. Related Work

The problem of joint antenna selection and beam scheduling was first formulated in [7], in which the authors showed that antenna selection incurs a complex optimization problem. Moreover, the authors in [7] developed different effective semidefinite relaxation-based user scheduling approaches to achieve near-optimal solutions for a moderate number of users. A low-complexity beam selection and user scheduling scheme were proposed in [8]. However, the authors considered a situation that only one strong beam direction is available. The beam division multiple access (BDMS) was developed

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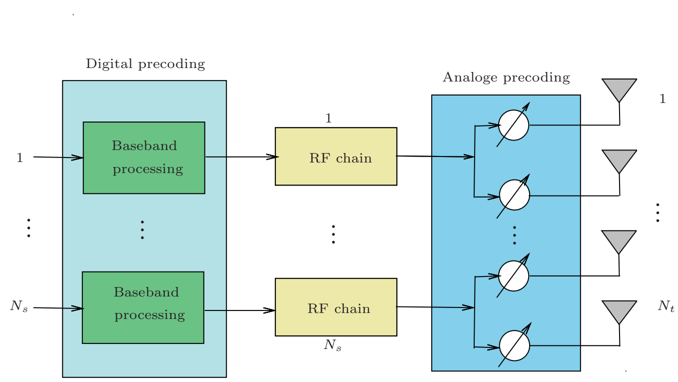

Figure 1: Hybrid beamforming ($N_{\mathrm{s}} < N_{\mathrm{u}}$).

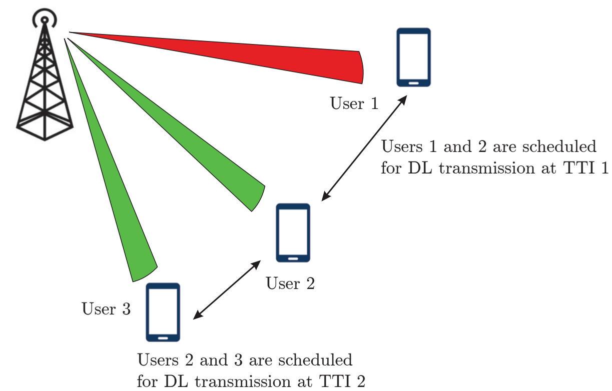

Figure 2: User scheduling for $N_{\mathrm{u}} = 3$ and $N_{\mathrm{s}} = 2$. In TTIs of T_1 and T_2, only 2 users are scheduled for downlink transmission.

in [9]. In the BDMS, the users with the strongest channel gain are scheduled for transmission. Thus, the performance is suboptimal in terms of throughput since it ignores the effect of multi-user interference. An antenna selection scheme in combination with the genetic algorithm (GA) for a large number of transmit antennas has been investigated in [10], in which a fast antenna selection algorithm was proposed. In [11], the authors developed a fast antenna selection method for massive MIMO based on Monte Carlo tree search.

The authors in [12] investigated beam selection using reinforcement learning for vehicle-to-infrastructure communication. Situational awareness beam selection based on machine learning for vehicular communication was studied in [13]. A low-complexity beam selection by exploiting a certain sparsity of millimeter wave (mmWave) channels was developed in [14]. The problem of beam scheduling based on effective network throughput maximization was studied in [15]. A new joint user scheduling and beam selection method based on the statistical channel state information (CSI) has been proposed in [16].

B. Motivation

Fully digital beamforming techniques require one radio frequency (RF) chain per antenna; thus, it incurs high power consumption and cost. The hybrid beamforming technique, which is the combination of digital precoding at the baseband and analog beamforming in the RF domain, is employed to solve this problem. Hybrid beamforming employs a reduced number of RF chains; hence, user scheduling is adopted to support a large number of devices [17]. The block diagram of hybrid beamforming is shown in Fig. 1. The optimal user scheduling is an NP-hard problem, which may incur a high power consumption at BS and delay for user scheduling. While the existing heuristic algorithms for antenna selection are practical for a low number of transmit antennas, they become inefficient for user selection in massive MIMO systems, where the number of users is vast. Hence, developing a fast and low-complexity user scheduling method based on the instantaneous channel quality is required.

C. Contributions

We develop fast and low-complexity user scheduling methods for a massive MIMO system, including 1) deep learning-reduced search (DL-RS), 2) statistical DL-RS (S-DL-RS), and 3) deep learning-genetic algorithm (DL-GA). The proposed methods exhibit the following advantages:

- The DL-RS method relies on DL to reduce the size of the search space;
- The statistical DL-RS method relies on the first-order statistics of the DNN output in the DL-RS method to further reduce the computational complexity of the DL-RS;
- The DL-RS and S-DL-RS methods are designed to achieve extremely low outage probability with low computational complexity;
- The iterative DL-GA user scheduling method intelligently creates the initial population of the GA based on DL to accelerate the convergence of the conventional GAs;
- The DL-GA is designed to achieve ergodic capacity with low computational complexity.

II. System Model

We consider a downlink single-cell multi-user massive MIMO network with N_{u} single-antenna users distributed in the cell. The BS employs hybrid beamforming with N_{s} RF chains, where $N_{\mathrm{s}} < N_{\mathrm{u}}$ holds, and thus, the BS needs to schedule N_{s} out of N_{u} users in each transmission time interval (TTI). Fig. 2 shows that a BS schedules two users for downlink transmission in TTIs of T_1 and T_2.

Let us consider that the BS schedules the users with indices $k_1, k_2, \ldots, k_{N_{\mathrm{s}}}$, in which $k_n \in \{1, 2, \ldots, N_{\mathrm{u}}\}$, for downlink data transmission during the T-th TTI. The received baseband signal at the k_n-th user can be written as [18]

$$r_{k_n} = \mathbf{h}_{k_n}^{\mathrm{H}} \left(\sum_{i=1}^{N_{\mathrm{s}}} \mathbf{w}_{k_i} s_{k_i} \right) + v_{k_n}, \quad n \in \{1, 2, \ldots, N_{\mathrm{s}}\}, \quad (1)$$

where $\mathbf{h}_{k_n} \triangleq [h_{k_n 1}\ h_{k_n 2}\ \ldots h_{k_n N_{\mathrm{t}}}]^T \in \mathbb{C}^{N_{\mathrm{t}} \times 1}$ is the vector of the channel between the N_{t} transmit antennas and k_n-th user, $\mathbf{w}_{k_i} \in \mathbb{C}^{N_{\mathrm{t}} \times 1}$ is the beamforming vector associated with the k_i-th user, $s_{k_i} \in \mathbb{C}$ is the data signal with unit power intended for user k_i, and v_{k_n} is additive white Gaussian noise (AWGN) with zero-mean and variance σ_{v}^2 at the k_n-th user. We assume that $\mathbf{h}_{k_n}$, $k_n \in \{1, 2, \ldots, N_{\mathrm{u}}\}$ is known at the BS, and it remains constant during each user scheduling process, but it independently varies for the next user scheduling TTI. We model the channel vector $\mathbf{h}_{k_n}$ by a complex-Gaussian random vector with mean vector $\boldsymbol{\mu}_{k_n}$ and covariance matrix $\mathbf{C}_{k_n}$ as

$$\mathbf{h}_{k_n} \sim \mathcal{CN}\big(\boldsymbol{\mu}_{k_n}, \mathbf{C}_{k_n}\big). \tag{2}$$

If $\boldsymbol{\mu}_{k_n} \neq 0$, there is a line-of-sight (LoS) link between the BS and user k_n. In this case, beamforming can be seen as a signal beam towards user k_n.

The BS schedules the users in each TTI to maximize the sum-rate capacity. The sum-rate capacity for the scheduled users with indices $k_1, k_2, \ldots, k_{N_\mathrm{s}}$ can be expressed as

$$R = \sum_{m=1}^{N_\mathrm{s}} \log\left(1 + \gamma_{k_m}\right), \tag{3}$$

where γ_{k_m} is the instantaneous SINR at user k_m, $m \in \{1, 2, \ldots, N_\mathrm{s}\}$, which can be written as follows

$$\gamma_{k_m} \triangleq \frac{\left|\mathbf{h}_{k_m}^{\mathrm{H}} \mathbf{w}_{k_m}\right|^2}{\sum\limits_{i \in \mathcal{N}_\mathrm{s}} \left|\mathbf{h}_{k_m}^{\mathrm{H}} \mathbf{w}_{k_i}\right|^2 + \sigma_\mathrm{v}^2}, \tag{4}$$

and $\mathcal{N}_\mathrm{s} = \{1, 2, \ldots, N_\mathrm{s}\}/\{m\}$.

The problem of user scheduling at the BS can be formulated as follows

$$\begin{aligned} &\underset{\{k_1, k_2, \ldots, k_{N_\mathrm{s}}\}}{\operatorname{argmax}} \sum_{m=1}^{N_\mathrm{s}} \log\left(1 + \gamma_{k_m}\right) \\ &\text{s.t.} \quad \{k_1, k_2, \ldots, k_{N_\mathrm{s}}\} \subseteq \{1, 2, \ldots, N_\mathrm{u}\}. \end{aligned} \tag{5}$$

As it can be seen in (5), optimal user scheduling is an NP-hard problem, which requires exhaustive search. This results in high power consumption at the BS to find the optimal schedule for large combinations of $\binom{N_\mathrm{u}}{N_\mathrm{s}}$. In addition, it may incur a considerable delay in user scheduling, which hinders efficient scheduling.

III. DL-based Beam Scheduling

In this section, we first propose the DL-RS user scheduling method by using supervised DL. Then, a statistical version of the DL-RS is developed. Finally, the proposed DL-RS and its statistical version are combined with GA. While the idea behind the proposed user scheduling methods is to reduce computational complexity, they are designed for different scenarios. The first and second scheduling methods are developed to offer low outage probability for static users, and the third method is designed to achieve outage capacity for dynamic users.

A. DL-RS User Scheduling

The problem of user scheduling using DL can be formulated as a classification problem, where the DNN directly outputs the indices of the users that maximize the sum-rate capacity. In the classification formulation, the users are encoded as a one-hot vector, i.e., a $\binom{N_\mathrm{u}}{N_\mathrm{s}}$-dimensional vector, where only one of its elements is equal to one and others are zero. The index of the non-zero element determines the set of optimal users. However, it becomes impractical for large users since a DNN with an output layer of size $\binom{N_\mathrm{u}}{N_\mathrm{s}}$ is required. Moreover, the training complexity is significantly high in the classification formulation since the DNN needs to be trained by every $\binom{N_\mathrm{u}}{N_\mathrm{s}}$ user combination at least once. In this paper, we formulate user scheduling as a regression problem to obtain decision boundaries in order to separate the users into two subsets. Unlike the classification formulation, the DNN output size in our solution is reduced to two and it is used to reduce the size of the user set to be searched. Furthermore, in our solution, the DNN does not need to be trained over all possible $\binom{N_\mathrm{u}}{N_\mathrm{s}}$ user combinations in the training phase.

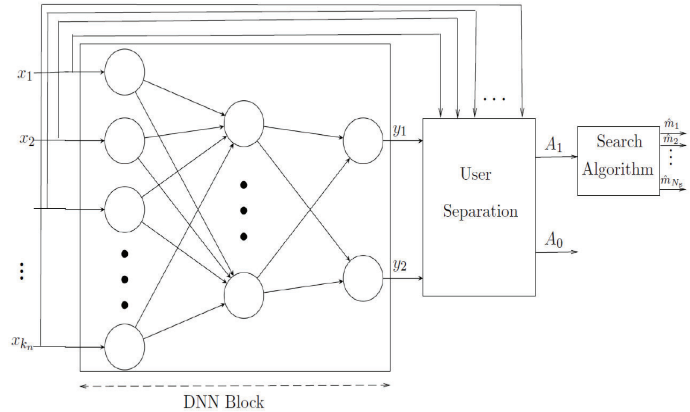

Figure 3: Block diagram of the proposed DL-RS user scheduling method.

Fig. 3 illustrates the block diagram of the proposed DL-RS user scheduling method. As this figure shows, it comprises of three blocks: 1) DNN block, which obtains decision boundaries; user separation block, which restricts the user set to be searched to set $\mathcal{A}_1$ with lower cardinality; and search algorithm that obtains the optimal users from the set $\mathcal{A}_1$.

Let us define the signal plus interference power (SPIP) of the k_n-th user as follows

$$x_{k_n} \triangleq \sum_{m=1}^{N_\mathrm{s}} \left|\mathbf{h}_{k_n}^{\mathrm{H}} \mathbf{w}_{k_m}\right|^2. \tag{6}$$

Since $\mathbf{h}_{k_n}$ and $\mathbf{w}_{k_m}$ are continues random vectors, and $\mathbf{h}_{k_n}$ and $\mathbf{h}_{k_m}$ are independent, the probability that x_{k_n} and x_{k_m}, $n \neq m$, are equal is zero for each TTI. Hence, the SPIP can uniquely identify the index of the users when the value of $\mathbf{h}_{k_n}$ and $\mathbf{w}_{k_m}$ are known at the BS. Hence, we employ x_{k_n} as the identifier of the k_n-th user. Let us write $\{m_1, m_2, \ldots, m_{N_\mathrm{s}}\}$ as

$$\begin{aligned} \{m_1, m_2, \ldots, m_{N_\mathrm{s}}\} = &\underset{\{k_1, k_2, \ldots, k_{N_\mathrm{s}}\}}{\operatorname{argmax}} \sum_{m=1}^{N_\mathrm{s}} \log\left(1 + \gamma_{k_m}\right) \\ &\text{s.t.} \quad \{k_1, \ldots, k_{N_\mathrm{s}}\} \subseteq \{1, \ldots, N_\mathrm{u}\}. \end{aligned} \tag{7}$$

Now, by using (7) and (6), we define the highly nonlinear function $\mathbf{f} : \mathbb{R}^{N_\mathrm{u}} \to \mathbb{R}^2$ as follows

$$\mathbf{f}\big(x_1, x_2, \ldots, x_{N_\mathrm{u}}\big) = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} \min(x_{m_1}, x_{m_2}, \ldots, x_{m_{N_\mathrm{s}}}) \\ \max(x_{m_1}, x_{m_2}, \ldots, x_{m_{N_\mathrm{s}}}) \end{bmatrix}, \tag{8}$$

where $m_1, m_2, \ldots, m_{N_\mathrm{s}} \in \{1, 2, \ldots, N_\mathrm{u}\}$ are the indices of the optimal users maximizing the sum-rate capacity in (7).

If we design and train a DNN that can capture the relation in (8), then, given y_1 and y_2, the search space can be reduced to

$$\{m_1, m_2, \ldots, m_{N_\mathrm{s}}\} = \{k \mid y_1 \leqslant x_k \leqslant y_2, x_k \in \mathcal{X}_\mathrm{u}\}, \quad (9)$$

where

$$\mathcal{X}_\mathrm{u} = \{x_1, x_2, \ldots, x_{N_\mathrm{u}}\}. \quad (10)$$

Here, we design and train a DNN that accepts the SPIP of the N_u users as its input sequence as follows

$$\mathcal{X} = \{x_{k_1}, x_{k_2}, \ldots, x_{k_{N_\mathrm{u}}}\}, \quad (11)$$

where $k_1, k_2, \ldots, k_{N_\mathrm{u}} \in \{1, 2, \ldots, N_\mathrm{u}\}$ and $x_{k_1} \leqslant x_{k_2} \leqslant \cdots \leqslant x_{k_{N_\mathrm{u}}}$. Our design objective is to learn y_1 and y_2 in (8) at the output of the DNN. The values of y_1 and y_2 provide a decision boundary as in (9) that can reduce the number of users to be searched. Using y_1 and y_2, we can divide the index of users, i.e., $\mathcal{B} \triangleq \{1, 2, \ldots, N_\mathrm{u}\}$ into two subsets of $\mathcal{A}_1 = \{u_1, u_2, \ldots, u_{N_1}\}$ and $\mathcal{A}_0 = \mathcal{B} - \mathcal{A}_1$. Ideally, the subset $\mathcal{A}_1$ contains N_s users, and it is the optimal user set. However, since the DNN with P complexity is an approximator, the cardinality of $\mathcal{A}_1$ can be higher or lower than N_s, and also, there is always a non-zero probability that $\mathcal{A}_1$ does not include the N_s indices of the optimal user set. Hence, our DL-RS method may not reach the optimal solution.

Designing a DNN with a suitable layer structure can provide performance close to the optimal one with significantly lower computational complexity since the decision boundaries can be learned in such a way that $\mathcal{A}_1$ contains a few numbers of user indices (close to N_s), including the indices of the optimal user set. After user separation by using y_1 and y_2, we encounter two situations. When $N_1 \geqslant N_\mathrm{s}$, we implement $\binom{N_1}{N_\mathrm{s}}$ number of searches to obtain the maximum sum-rate capacity of the beams in $\mathcal{A}_1$. When $N_1 < N_\mathrm{s}$, we keep the N_1 users in $\mathcal{A}_1$ and add to it the $N_\mathrm{s} - N_1$ users in $\mathcal{A}_0$ that their corresponding SPIP is closest to the decision boundaries y_1 and y_2. Finally, we consider the achieved set as the solution to the user scheduling problem. It is worth mentioning that as $\binom{N_\mathrm{u}}{N_\mathrm{s}}$ increases, the efficiency of the DL-RS user scheduling method is enhanced since the complexity is dominated by the number of searches rather than the computational complexity of the DNN.

B. Training Procedure

To train the DNN, we need to collect a sufficient number of training samples. For real data, we first need to estimate the $N_\mathrm{t} \times N_\mathrm{u}$ CSI. Then, we form the sorted input sequence $\mathcal{X}$ in (11) based on the SPIP in (6) by applying the desired beamforming technique. In the next step, we compute the sum-rate capacity for all possible combinations and obtain the index of the optimal user set. The output of the DNN, y_1, and y_2, for each training sample, is labeled as in (8) by using the SPIP of the optimal user set.

Considering $\mathcal{X}^{(i)}$ and $\mathbf{y}^{(i)} \triangleq [y_1^{(i)}, y_2^{(i)}]$ as the input and output of the DNN for the i-th training sample, the training set is generated as follows

$$\left\{(\mathcal{X}^{(1)}, \mathbf{y}^{(1)}), (\mathcal{X}^{(2)}, \mathbf{y}^{(2)}), \ldots, (\mathcal{X}^{(N_\mathrm{a})}, \mathbf{y}^{(N_\mathrm{a})})\right\}, \quad (12)$$

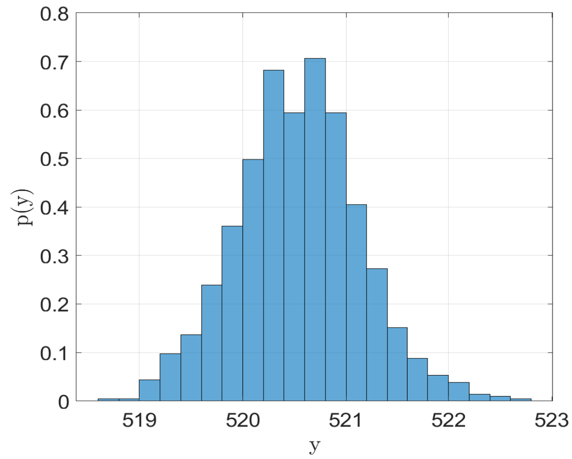

Figure 4: The histogram of the learned decision boundary y_1.

where N_a is the number of training samples. This data set is feed to the designed DNN to learn the non-linear relation between $\mathbf{y}$ and $\mathcal{X}$ in (8) as

$$\mathbf{y} = \Phi(\mathcal{X}, \boldsymbol{\theta}), \quad (13)$$

where $\boldsymbol{\theta}$ includes the DNN weights and biases that are learned during the training procedure. Finally, the trained DNN is employed for real-time user scheduling. Fig. 3 shows the structure of the employed DNN for $N_\mathrm{u} = 32$ and $N_\mathrm{s} = 4$. Based on the values of N_u and N_s, the number of hidden layers of the DNN can vary in order to achieve a higher outage capacity. In our designed DNN, a clipped ReLU (CReLU) activation function with the clipping ceiling equals to 1 is exploited.

C. Statistical DL-RS User Scheduling

Fig. 4 illustrates the histogram of the boundary region y_1 in the test phase of the DNN. As can be observed, the values of y_1 are accumulated around its mean $\mu_1 = \mathbb{E}\{y_1\}$. This offers that we can further reduce the complexity of the DL-RS user scheduling combinatorial optimization problem by using this mean value instead of using the output of the trained DNN for user separation. The reduced complexity is obtained at the expense of performance degradation in terms of outage capacity and ergodic capacity.

Let us consider the trained DNN as $\mathbf{y} = \Phi(\mathcal{X}, \boldsymbol{\theta})$. We evaluate this function for N_e samples, $\mathcal{X}_k$, $k = 1, 2, \ldots, N_\mathrm{e}$, and obtain its sample mean as follows

$$\boldsymbol{\mu} = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} = \frac{1}{N_\mathrm{e}} \sum_{k=1}^{N_\mathrm{e}} \Phi(\mathcal{X}_k, \boldsymbol{\theta}). \quad (14)$$

In the statistical DL-RS, we use μ_1 and μ_2 instead of y_1 and y_2 in real-time user scheduling to identify $\mathcal{A}_1$ as

$$\mathcal{A}_1 = \{k \mid \mu_1 \leqslant x_k \leqslant \mu_2, x_k \in \mathcal{X}_\mathrm{u}\}, \quad (15)$$

where $\mathcal{X}_\mathrm{u}$ is given in (10). Restricting the search space to $\mathcal{A}_1$ reduces the computational complexity at the expense of a suboptimal solution.

D. DL-GA User Scheduling

GA has been widely employed to solve antenna selection problems. GA employs random elements within an algorithm for dealing with combinatorial optimization problems. Population initialization is the first step in the GA. There are two main methods to initialize a population in a GA; 1) random initialization, where the initial population, the first generation, is usually created randomly; and 2) heuristic initialization, where the initial population is created using a known heuristic for the specific problem. It has been shown that the convergence rate of the GAs is highly affected by the initial population.

Our developed DL-RS and statistical DL-RS user scheduling methods can provide a suitable initial population for GAs to improve their performance in terms of convergence speed and computational complexity. In the proposed DL-GA user scheduling method, either the obtained users based on the decision boundaries y_1 and y_2 learned by DNN, i.e., $\mathcal{A}_1 = \{u_1, u_2, \ldots, u_{N_1}\}$ or the users obtained based on μ_1 and μ_2 in (15) are used as the initial population of GA. Let us assume that $N_1 = N_\mathrm{p} N_\mathrm{s} + N_\mathrm{r}$ holds, where $N_\mathrm{r} < N_\mathrm{s}$. In our solution, $N_\mathrm{p} + 1$ initial populations can be created as

$$\begin{aligned} \mathcal{P}_1 &= \{u_1, u_2, \ldots, u_{N_\mathrm{s}}\}, \\ \mathcal{P}_2 &= \{u_{N_\mathrm{s}+1}, u_{N_\mathrm{s}+2}, \ldots, u_{2N_\mathrm{s}}\}, \\ &\vdots \\ \mathcal{P}_{N_\mathrm{p}} &= \{u_{(N_\mathrm{p}-1)N_\mathrm{s}+1}, u_{(N_\mathrm{p}-1)N_\mathrm{s}+2}, \ldots, u_{N_\mathrm{p}N_\mathrm{s}}\}, \\ \mathcal{P}_{N_\mathrm{p+1}} &= \{u_{N_\mathrm{p}N_\mathrm{s}+1}, u_{N_\mathrm{p}N_\mathrm{s}+2}, \ldots u_{N_\mathrm{p}N_\mathrm{s}+N_\mathrm{r}}, \mathcal{P}_\mathrm{x}\}, \end{aligned} \tag{16}$$

in which $u_1, u_2, \ldots, u_{N_1} \in \mathcal{A}_1$. The remaining populations and $\mathcal{P}_\mathrm{x}$ are randomly selected from $\mathcal{A}_0 = \mathcal{B} - \mathcal{A}_1$.

Our extensive simulation experiments show that an efficient initial population selection strategy creates the initial population based on the ascending order of $\mathcal{A}_1$ instead of its random selection. Using the DL-RS or statistical DL-RS in combination with existing GAs for antenna selection, such as [10], lead to a faster convergence rate to the optimal solution in these algorithms, and therefore, it achieves lower computational complexity.

IV. Performance Evaluation

In this section, we evaluate the performance of the proposed DL-RS, statistical DL-RS, and DL-GA user scheduling methods through extensive simulation experiments.

A. Simulation Setup

We consider a BS with $N_\mathrm{t} = 128$ transmit antennas which can serve $N_\mathrm{u} = 32$ users. It is considered that the BS schedules $N_\mathrm{s} = 4$ beams that maximize the sum-rate capacity derived in (5). This results in 35960 scheduling combinations. Unless otherwise mentioned, we model the channel vector $\mathbf{h}_k$ by $\mathbf{h}_k \sim \mathcal{CN}(\mu_k \mathbf{1}_k, \sigma_\mathrm{k}^2 \mathbf{I}_k)$, $k = 1, 2, \ldots, 32$, where $\mathbf{h}_k$ and $\mathbf{h}_m$, $k \neq m$, are independent random vectors.

We assume that the maximum ratio transmission (MRT) beamforming technique, i.e., $\mathbf{w}_k = \mathbf{h}_k / \|\mathbf{h}_k\|$, is employed at the BS. The desirable system performance is set to 5% outage probability, and the average signal-to-noise ratio (SNR) is defined as

$$\gamma \triangleq \frac{\frac{1}{N_\mathrm{s}} \sum_{k=1}^{N_\mathrm{s}} (\mu_k^2 + \sigma_k^2)}{\sigma_\mathrm{v}^2}. \tag{17}$$

For performance comparison, we consider the recently proposed fast GA antenna selection method in [10]. We apply our DL-based initial population selection methods to this GA algorithm and develop our DL-GA and its statistical version. We evaluate the performance of the proposed beam scheduling methods in terms of outage probability and ergodic capacity for 10^4 Monte Carlo trials.

Table I: Training phase parameters.

Parameter	**Value**
Number of batches	50
Size of batches	100
Number of epoches	40
Number of iterations	2000

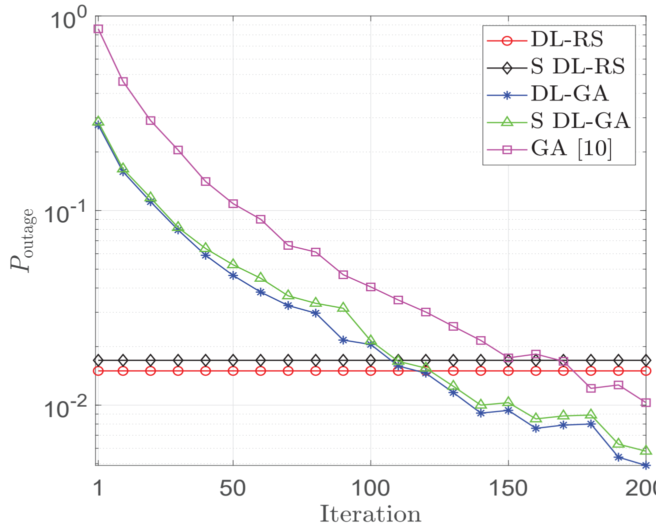

Figure 5: Outage probability versus the number of iterations in a network with 32 users and a BS that has $N_\mathrm{t} = 128$ transmit antennas and $N_\mathrm{s} = 4$ beams (S stands for statistical).

Table I summarizes the parameters for the training phase of the employed DNN in Fig. 4. We consider 5×10^3 training samples, and the ADAM optimization method is applied with the initial learning rate of 0.01 [19]. Our developed DL-RS requires 5120 elementary operations (sum and multiplication) for DNN forward propagation computation. On the other hand, the number of elementary operations for each search is 504 (excluding the complexity of search and sorting); hence, the computational complexity of our used DNN is equivalent to $5120/504 \approx 11$ number of searches.

B. Simulation Results

Fig. 5 shows the outage probability of the proposed DL-RS, statistical DL-RS, DL-GA, statistical DL-GA, and the fast GA beamforming methods proposed in [10] versus the number of iterations at $\gamma = 20$ dB. It is assumed that $\mu = \mu_k = 1$, and $\sigma^2 = \sigma_k^2 = 1$, for $k = 1, 2, \ldots, 32$. Since our proposed DL-RS and statistical DL-RS methods are not an iterative algorithm, their outage probability is constant. As can be observed, all

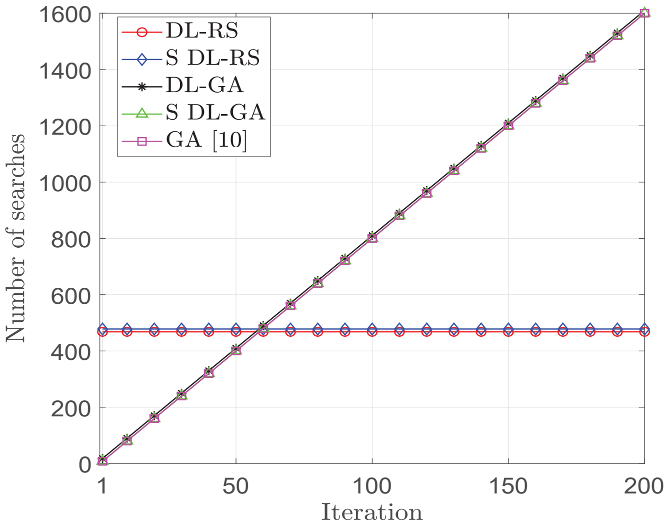

Figure 6: The average number of searches versus the number of iterations in a network with 32 users and a BS that has $N_\mathrm{t} = 128$ transmit antennas and $N_\mathrm{s} = 4$ beams (S stands for statistical).

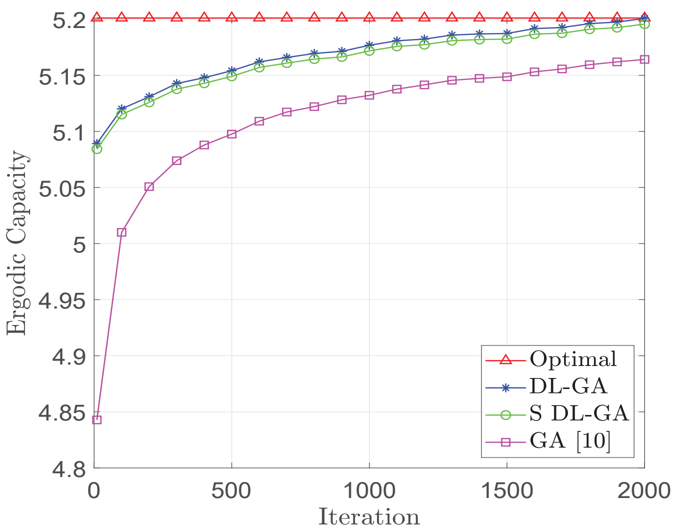

Figure 7: Ergodic Capacity versus the number of iterations in a network with 32 users and a BS that has $N_\mathrm{t} = 128$ transmit antennas and $N_\mathrm{s} = 4$ beams (S stands for statistical).

of our developed user scheduling methods exhibit very low outage probability and also outperform the DL-GA introduced in [10]. The corresponding average number of searches for the outage probability of these methods is shown in Fig. 6. As it can be seen from this figure, the average number of searches is very low. The average number of searches for the DL-RS and statistical DL-RS is 489 and 478, respectively. However, the number of searches in other methods linearly increases with the number of iterations since each iteration includes $N_\mathrm{u}/N_\mathrm{s} = 8$ number of searches.

Fig. 7 illustrates the ergodic capacity of the DL-GA, statistical DL-GA, and the fast GA [10]. As seen, the DL-GA and statistical DL-GA exhibit a faster convergence rate compared to the fast GA user scheduling method. This means that the proposed algorithms achieve the optimal user set solution with a lower number of searches. The reason is that the initial population in our methods is intelligently learned, whereas it is randomly selected in the method mentioned in [10].

V. Conclusion

In this paper, we proposed three user scheduling methods based on DL. The proposed methods reduce the number of users to be searched through a decision boundary that a DNN learns. More specifically, the decision boundary shrinks the search space. Furthermore, we developed the DL-GA user scheduling method that takes advantage of intelligent initial population selection based on DL. The effectiveness of the developed DL methods has been confirmed through extensive simulation experiments for a large number of users.

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