Journal of Information Systems Engineering and Management
2025, 10(17s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

Resource Allocation and Spectrum Sensing for 5G Networks Based on Deep Learning

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ARTICLE INFO

Received: 06 Dec 2024

Revised: 29 Jan 2025

Accepted: 12 Feb 2025

ABSTRACT

As wireless systems are increasingly utilized, the volume of data traffic in wireless networks continues to grow. To manage these demands and ensure quality service for each user, employing multiple-input multiple-output (MIMO) systems is seen as an effective approach for the future of telecommunications. Additionally, managing radio resources and controlling transmitted power are crucial in wireless systems. Various algorithms have been developed to address these power control challenges. Notably, machine learning algorithms are gaining traction for optimizing power allocation in MIMO systems because they offer lower computational complexity and faster processing times suitable for real-time applications. However, gathering training data for deep learning applications in telecommunications poses significant challenges. Deep neural networks require extensive data for training, and labeling this data is a complex process. In this paper, we explore a power allocation strategy in massive MIMO systems using a deep neural network that employs unsupervised learning, where a cost function updates the network instead of relying on labeled data. The objective is to maximize the signal-to-interference-plus-noise ratio (SINR). The findings demonstrate that unsupervised deep learning can effectively allocate power while reducing computational complexity and processing time.

Keywords: Multiple-input multiple-output, power allocation, deep neural network.

1- Introduction

In the evolving landscape of 5G networks, the integration of deep learning for resource allocation and spectrum sensing presents a transformative opportunity to enhance network performance and efficiency. The application of massive MIMO and mmWave technologies has been foundational in the advancement of 5G, with significant benefits and challenges identified in terms of spectral and energy efficiency, as well as hardware requirements [1][3][9]. The deployment of these technologies requires innovative approaches to manage the increased complexity and dynamic nature of 5G networks. Deep learning has emerged as a potent tool for optimizing resource allocation in these complex environments. Sanguinetti et al. highlighted the potential of deep learning in power allocation within massive MIMO systems, which is crucial for maximizing network throughput and minimizing interference [4]. This approach is supported by further studies that suggest deep learning can effectively handle the variable and high-dimensional data characteristic of 5G networks, optimizing resource distribution in real-time [20][17]. Spectrum sensing, another critical aspect of resource management in 5G, also benefits from deep learning techniques. The ability to predict and adapt to the spectral environment allows for more efficient use of bandwidth and improves the overall quality of service. Techniques like unsupervised learning provide frameworks for developing adaptive algorithms that can enhance spectrum sensing without the need for extensive labeled data, which is often scarce in real-world scenarios [28][30]. Moreover, deep learning has been applied to specific challenges within 5G, such as non-orthogonal multiple access (NOMA) schemes, where it helps in managing co-channel interference and power allocation to maximize spectral efficiency [23]. Similarly, the integration of deep learning in mmWave communications assists in beamforming and channel estimation, which are critical for exploiting the high-speed potential of mmWave frequencies [8][6]. The potential of deep learning extends to various other applications within 5G networks, such as caching and interference alignment, which are essential for enhancing network reliability and throughput [22][26]. Additionally, the iterative improvements in deep learning models, such as those introduced by Kingma and Ba with the Adam optimizer, provide robust methods for training deep neural networks efficiently, which is vital for deploying complex models in dynamic network environments [32]. The benefits of integrating deep learning are especially apparent in the context of dynamic spectrum management, where it can predict network loads and optimize frequency allocation in real-time, significantly enhancing user experiences and network efficiency [17][20]. Deep learning's role in optimizing physical layer operations, such as encoding and decoding processes, also demonstrates its critical impact on improving the throughput and reliability of 5G networks. Techniques like deep reinforcement learning offer promising results in areas such as power control and signal optimization, which are crucial for maintaining service quality in dense urban environments with high user mobility [14][25]. Furthermore, the use of deep learning for security purposes in 5G networks cannot be understated. With the increasing number of connected devices and the surge in data traffic, securing these networks against a wide range of threats is paramount. Deep learning algorithms help in anomaly detection and in developing robust security frameworks that adapt to evolving threats without compromising network performance [17][18]. In addition to enhancing network operations, deep learning also facilitates the development of user-centric applications, such as personalized streaming and dynamic content delivery, by intelligently predicting user preferences and network conditions. This not only improves user satisfaction but also optimizes network resource usage, which is a critical concern for service providers aiming to reduce operational costs while improving service delivery [27][23]. Deep learning's role in optimizing physical layer operations, such as encoding and decoding processes, also demonstrates its critical impact on improving the throughput and reliability of 5G networks. Techniques like deep reinforcement learning offer promising results in areas such as power control and signal optimization, which are crucial for maintaining service quality in dense urban environments with high user mobility [14][25]. Furthermore, the use of deep learning for security purposes in 5G networks cannot be understated. With the increasing number of connected devices and the surge in data traffic, securing these networks against a wide range of threats is paramount. Deep learning algorithms help in anomaly detection and in developing robust security frameworks that adapt to evolving threats without compromising network performance [17][18]. In addition to enhancing network operations, deep learning also facilitates the development of user-centric applications, such as personalized streaming and dynamic content delivery, by intelligently predicting user preferences and network conditions. This not only improves user satisfaction but also optimizes network resource usage, which is a critical concern for service providers aiming to reduce operational costs while improving service delivery [27][23]. As 5G networks continue to evolve, leveraging the capabilities of deep learning will be essential in addressing the complexities and challenges associated with next-generation wireless systems. The ongoing research and development in this field promise to yield further innovations that will enhance the scalability, efficiency, and security of 5G networks, ultimately leading to more robust and user-friendly communications systems [26][28].

2- Research background

Massive MIMO refers to a telecommunications technology where a base station is equipped with a large number of antennas and serves a very large number of users using spatial multiplexing. In recent years, significant advancements have been made in the utilization of this technology. In the industry, this technology has been integrated into the new radio standard G5 [26]. In this work, the use of deep neural networks for solving the power allocation problem using the max-product method in a massively parallel input-output link network has been employed. The neural network is utilized to optimize user positions to achieve near-optimal efficiency. While traditional algorithms based on precise mathematical models can provide satisfactory performance, they may not be suitable for real-time applications due to computational complexity delays. In fact, demands with minimal delays and low power consumption in next-generation wireless systems are becoming increasingly common. The potential of neural networks in feature extraction and presentation has garnered significant attention in the field of wireless communications.

[27], [28] are technologies using deep learning that demonstrate a process of offline learning followed by online utilization of the trained network. Compared to repetitive algorithms, these technologies significantly reduce time complexity. As the trained network only consists of simple linear and non-linear transformation units, the complexity of power allocation decreases fundamentally, enabling real-time power allocation execution, such as tracking users' position changes.

In this paper, initially, a deep neural network is trained to learn the mapping between user locations and optimal resource allocation based on [4]. Subsequently, the trained neural network is used for predicting the allocated capacity to a set of new users. The significant improvement in performance complexity is achieved by utilizing deep learning. The applied method can ensure near-optimal efficiency. Furthermore, to enhance this process, an unsupervised neural network learning algorithm is utilized. The utilization of deep learning in telecommunication data collection and neural network training poses a significant challenge as neural networks require large volumes of data for learning, making the labeling process for this high volume of training data complex. Instead of labels, a cost function is employed here to update the deep neural network. The performance of both supervised and unsupervised deep neural network training methods is evaluated to achieve near-optimal efficiency.

2.1 System Model

Considering the down link system as described in [4], we consider a massive multiple-input multiple-output network with L cells, each containing a base station with M antennas and K users. $h_{ij}^{l} \in C^{M}$ represents the channel between user i in cell l and base station j, and we assume:

$$h_{li}^{j} \sim N_C\ (0_M . R_{li}^{j}) \qquad (1\text{-}2)$$

Where $R_{li}^{j} \in C^{M\times M}$ is the known spatial correlation matrix at base station j. Based on 2.3, the average channel gain from one antenna at base station j to user i in cell l is expressed as follows:

$$\beta_{li}^{j} = \gamma - 10\ \alpha\ log_{10}\left(\frac{d_{li}^{j}}{1km}\right)\ \ dB \qquad (1\text{-}2)$$

where γ =-148 and α =3.76 are considered. Additionally, $d_{li}^{j}$is the distance of user i in cell l from base station j. It is defined as $d_{1i}^{j} = \left\|x_{1i}^{j}\right\|$, where $x_{1i}^{j} \in R^2$ represents the spatial location of the user in Euclidean space. Similar to [4], channel training with the use of pilots is employed for estimating channel vectors at base station j. The base station and users operate using TDD protocol. In the base station, the standard method of MMSE channel estimation is utilized to obtain the channel estimate h_{li}^{j}.

2.1.1 Spectral Efficiency in downlink

The base station in cell 1 sends the down link signal $X_1 = \sum_{i=1}^{K} W_{1i}\zeta_{1i}$, where $\zeta_{1i} \sim N_C\ (0_M . \rho_{1i})$is the data signal of the uplink for user i in cell 1, accompanied by the precoding vector $W_{1i} \in C^{M}$ specifying the spatial direction of the transmitter, is defined. The pre coding vector ensures condition $E\{\|\omega_{1i}\|^2\} = 1$, where $\rho_{1i}$is the allocated transmit power to the user. The spectral efficiency of the downlink for user k in cell j, considering 2.16, is defined as follows:

$$SE_{jk}^{dl} = \frac{\tau_d}{\tau_c}\log_2\left(1 + \gamma_{jk}^{dl}\right) \quad (bit/\ s/Hz) \qquad (3\text{-}2)$$

Where SINR is as follows: [4]

$$SE_{jk}^{dl} = \frac{\rho_{jk}\left|E\{\omega_{jk}^{H} h_{jk}^{j}\}\right|^2}{\sum_{l=1}^{L}\sum_{i=1}^{k_l}\rho_{li}\left|E\{\omega_{li}^{H} h_{jk}^{l}\}^{H}\right|^2 - \rho_{jk}\left|E\{\omega_{jk}^{H} h_{jk}^{l}\}^{H}\right|^2 + \sigma^2} \qquad (4\text{-}2)$$

The coefficient before the logarithm ($\frac{\tau_d}{\tau_c}$) is the ratio of the samples used for the uplink data per each coherence block. It is important to note that this high band is accessible for channels that have implemented channel hardening [3].

2.1.2 Design of Pre coder

Precoding at the transmitter can be used in downlink links to focus each signal on a terminal's desired usage. Unlike uplink links, finding an optimized pre coder in downlink links poses a challenge because the spectral efficiency in downlink links depends on pre coding vectors used by all users in the network as a whole. Due to the bidirectional nature of uplink and downlink channels in Time-Division Duplexing (TDD) mode, there is a strong relationship between the receiver combiner in the uplink and the transmitted precoding in the downlink. Inspired by the up-down link duality method in Eq. 2-2, the X precoding vector can be selected as follows:

$$\omega_{jk} = \frac{v_{jk}}{\left\|v_{jk}\right\|} \qquad (5\text{-}2)$$

where v_{jk} specifies the received combiner vector identifying the usage of the transmitted signal from the uplink by user k in cell j. In this process, v_{jk} is chosen to maximize the selected rate based on the combiner method, which utilizes channel estimation of each terminal to maximize the power and strength of the desired signal from that terminal [29].

$$v_{jk}^{MR} = \hat{h}_{jk}^{j} \tag{6-2}$$

The choice of this pre-encoding method is because it has the least complexity among the combined methods, but yields a suboptimal result.

3- Proposed Method

3.1 Problem Formulation

The downlink spectral efficiency for user k in cell j is defined as in Eq. 3-1. As mentioned in previous Section, among various power allocation techniques, the max product SINR method is utilized. In fact, the main objective is to maximize the SINR product of all users, which can be formulated as follows:

$$\max_{\{\rho_{jk}:\,\forall\, j.k\}} \prod_{j=1}^{L} \prod_{k=1}^{K} \gamma_{jk}^{dl}$$
$$subject\ to \sum_{k=1}^{K} \rho_{jk} \leq p_{max}^{dl}. \quad j = 1.\cdots.L \tag{1-3}$$

Where P_{max}^{dl} determines the maximum transmitting power of the downlink. In [4], initially, the Monte Carlo method presented in the following is used for calculating optimal powers:

1) Macroscopic Diffusion Effects:

a) Randomly delete the user deletes at position X_{1i}^{j}.

b) Calculation of the large-scale fading coefficients β_{lk}^{j}.

c) Calculation of the channel correlation matrix R_{1k}^{j}.

2) Microscopic Diffusion Effects:

a) Generation of a random channel estimate vector using the MMSE estimator.

3) Spectral Efficiency Calculation:

a) Calculation of the pre-coding vectors MR.

b) Channel estimate averaging for calculating the channel gain and interference mean gain.

4) Power Allocation with Solution 4-7

Solution 4.7 is obtained through geometric programming. However, polynomial complexity is required for its resolution. When the solution must be obtained promptly, even polynomial complexity can be considerable. In other words, the presented solution must be so rapid that it can be implemented in the system before user positions change, necessitating a re-solving of the power allocation problem.

3.2 Resource Allocation based on Supervised Deep Learning

The supervised learning approach functions as an approximation tool, training the neural network to approximate the accurate output as closely as possible. In this process, initially [4] using spatial information from users, which have the key features of channel propagation and interference in the network, is employed. Therefore, for each cell j, the learning problem is unknown mapping between the solution of 4-7, $\rho_j^* = [\rho_{j1}^*.\cdots.\rho_{jK}^*] \in R^K$, and the position of the 2KL user ($X = \{\rho_{1i}^{j}; \forall j.l.i\} \in R^{2KL}$. This is achieved by the well-known feature of neural networks, which are global approximation functions. A feed-forward neural network is considered, which consists of: an input layer with dimensions 2KL, N hidden layers, and an output layer with dimensions K+1. Ultimately, the network provides an optimal power allocation vector estimate. As observed, the size (number of neurons) of the output layer is K+1 instead of K, as we aim for the neural network to also learn $\sum_{k=1}^{K} \rho_{jk}^{*}$for enforcing power allocation constraints in Eq. 4-7 and achieving high estimation accuracy. The problem involves learning the weights and biases of the network, thereby reducing the mapping of input to output in the neural network, following the conventional mapping approach. Here, a training set is required, including N_T optimal power allocation samples for the training input x(n). Considering $\hat{\rho}_j(n)$ as the output of the neural network, the learning process involves minimizing the cost function.

$$\min_{\omega.b} \frac{1}{N_T} = \sum_{n=1}^{N_T} l\ (\hat{\rho}_j(n).\ \rho_j^{*}(n)) \tag{2-3}$$

Where l (.,.) can be any measure of distance measurement between the output data of a neural network and labeled data. Accordingly, with the forward and backward propagation, the parameters ω and b are adjusted, enabling the network to predict for new input vectors that were not part of the training data.

3.2.1 Implementation of Online Learning and Complexity

The complexity of supervised deep learning methods mainly relies on the generation of training data. Assuming each layer has N_i neurons, the calculation of the output of the neural network only requires $\sum_{i=1}^{N+1} N_{i-1} N_i$ real multiplications. The learning process is carried out by implementing the gradient descent algorithm and the 4-4-1-3 back propagation algorithm. However, in this method, for the generation of training data, we need to execute the optimal power allocation algorithm offline to find the desired labels.

3.3 Power Allocation with Unsupervised Deep Learning

Power control is a means to prevent performance inequalities among users. Defining a suitable cost function enables optimizing the transmitted power to achieve the desired balance in users' Signal-to-Interference-Plus-Noise Ratio (SINR). Similar to the previous section, we will aim to maximize the product of SINRs. The unsupervised learning framework avoids the calculation and creation of labeled training data and accelerates the retraining of the neural network model when changes occur in the system and network. In this work, large-scale fading behavior is considered, while small-scale fading changes, which occur in milliseconds, are not taken into account; this ensures relatively stable power transmission capability.

3.3.1 Presentation Method Feature

In this case, only user location data has been utilized, noting that the channel model can be statistically defined as a function of distance. A deep learning model has been employed to train on a large dataset, ensuring that after training, all users have learned the same model. This enhances the feasibility of implementing the proposed method.

The decision-making time for power allocation has been reduced by minimizing computations. In supervised deep learning, the training process requires more time compared to unsupervised methods for label computations.

3.3.2 Cost Function

In deep learning, the cost function is a way to provide rewards or penalties for updating a deep neural network. Unlike the previous section where we had labeled data and considered the Mean Squared Error (MSE) as the objective function, calculating the difference between the estimated output of the neural network and the optimal power with the aim of minimizing it, in this continuation of the work without having the optimal output, we consider the loss function as the max product Signal-to-Interference-Plus-Noise Ratio (SINR). We seek to maximize the product of SINRs or equivalently take their logarithm. This can define the loss function with respect to [30] as follows:

$$Cost = \underbrace{\sum_{j=1}^{L} \sum_{k=1}^{K} \log\left(z_1 + \frac{1}{SINR_{jk} + z_2}\right)}_{Objective} + 0 \cdot 1 \underbrace{\sum_{j=1}^{L} \sum_{k=1}^{K} \log\left(\rho_{jk} - p_{max}\right)}_{Constraint} \tag{3-3}$$

To prevent the solution provided from focusing too much on users with very high or very low Signal-to-Interference-Plus-Noise Ratio (SINR) in the learning process, we introduce two small constant values to the cost function. The value of z_1=0.01 is added to reduce the impact of users with high SINR, and z_2=0.01 is added to reduce the impact of users with low SINR [30].

3.3.3 Deep Learning Process

If multiple models are tailored to different users, each model will be trained on a different dataset. In such a scenario, ambiguity arises concerning which model should be used for which user. The use of online learning instead of pre-trained models can introduce another issue. In online learning, the model is influenced by a large number of new data points, which can lead to over fitting. Therefore, using a single large model to achieve the same result is less suitable than employing multiple models.

Input data and labels are crucial components for successful deep learning. Deep learning is trained to produce an output that closely resembles the label of the input data. Hence, a successful learning process may not be guaranteed for unlabeled input data. However, the proposed method resolves this issue. Instead of using a fixed optimal solution-derived label, we utilize the deep learning cost function 4-9 as the cost function. In Algorithm 1, the Train () function is the core part of the learning process, where X is the input to the neural network, and the output is P, representing the assigned power to users. This output is then passed to the function 4-9. Subsequently, the Adam optimizer, by computing the derivatives of the cost function, follows the changes to minimize the cost function. Therefore, θ is adjusted by the optimizer to minimize the cost function.

Algorithm 1 Unsupervised Deep Neural Network

Input: input X, n-epoch, batch size

Output: P

1: Θ = Random-Initialization

2: **for** $i = 1, \ldots, n - epoch$ **do**

3: P,Θ = Train(X, Θ,batch size)

4: C = Cost(X, P)

5: Θ = Adamoptimizer(C)

6: **end for**

7: Return:P,Θ

4. Performance Evaluation

The assumptions of the problem, as discussed in the article [4], are considered as summarized in Table 4.2. The training and test data used were obtained from [31]. The neural network considered for deep supervised and unsupervised learning is described in Table 4-3.

It is assumed that k equals 5 users distributed randomly and uniformly in each cell. The results are averaged over 100 different user distributions. The bandwidth considered in these data is 20 MH. The total receiver noise power is -94 dBm.

The neural network uses a set of N_T comprising 340,000 independent samples of user locations ($x(n);\ n = 1.\cdots.N_T$) and optimal power allocation { $\rho_j^j(n);\ n = 1.\cdots.N_T\}$ for $j = 1.\cdots.L$ which is obtained through solving (4-7). 90% of the data is used for training and 10% for validation which is independent of the training data and is used for testing. 10000 samples, that are independent from the training data, are used for test. The learning rate is determined by trial and error.

To evaluate the improvement that the proposed method brings in reducing execution time and solving the power allocation problem, the execution time of the deep neural network algorithm without supervision for each set of random user locations is compared with the execution time and solving (4-7) using CVX in Table 4.1.

Table 4.1: Comparison table of execution time of two methods (Max-Prod CVX, Unsupervised-NN) in seconds.

	Max-prod CVX	Unsupervised-NN
CPU	2.7	1.58 × 10-4

Considering Table 4.1, the execution time and achieving results by allocating power using unsupervised deep learning algorithm is less than the execution time of solving the optimization problem with CVX. This is due to the reduced computational complexity in neural networks compared to optimization methods. Additionally, in comparison to supervised learning methods, there is no requirement for the time needed to generate labeled data to solve the optimization problem. Therefore, the proposed method has computational complexity superiority over the compared methods.

For performance evaluation, the power allocation results based on neural networks have been compared with the power allocation results using optimization problem solving. Initially, the cumulative distribution function of spectral efficiency for each user in downlink link has been illustrated. Fig. 4.1 demonstrates that the presented neural network has provided results close to the optimal. The slight discrepancy in matching can be explained as follows;

Even though the neural network is given the complete information of all users in the network, in the precursor coding of MR, power is allocated solely based on the desired signal, neglecting the use of all this information leading to a slight loss compared to the optimal method. When comparing the two approaches of supervised and unsupervised learning used for neural networks, we observe that the performance of the unsupervised deep learning method is closer to optimal compared to supervised deep learning. This is because the effectiveness of supervised deep neural network learning is limited by locally optimal solutions obtained by the Max Product optimization problem-solving approach and is focused on finding a mapping between defined inputs and outputs. On the other hand, the unsupervised deep neural network learning method aims to optimize this objective function itself.

Table 4.2: Parameters of an extensive multi-input-multi-output network

Cell area	1 km×1 km
Bandwidth	200 MHz
Number of cells	L = 4
Number of UEs per cell	K=5
UL noise power	-94 dBm
UL transmit power	20 dBm
Samples per coherence block	$\tau_c = 200$

Table 4.3: Neural Network Parameters

	Size	Activation Function
Input	40	-
Layer 1 (Dense	512	elu
Layer 2 (Dense)	256	elu
Layer 3 (Dense)	128	elu
Layer 4 (Dense)	128	elu
Layer5 (Dense)	5	elu
Output	6	Linear

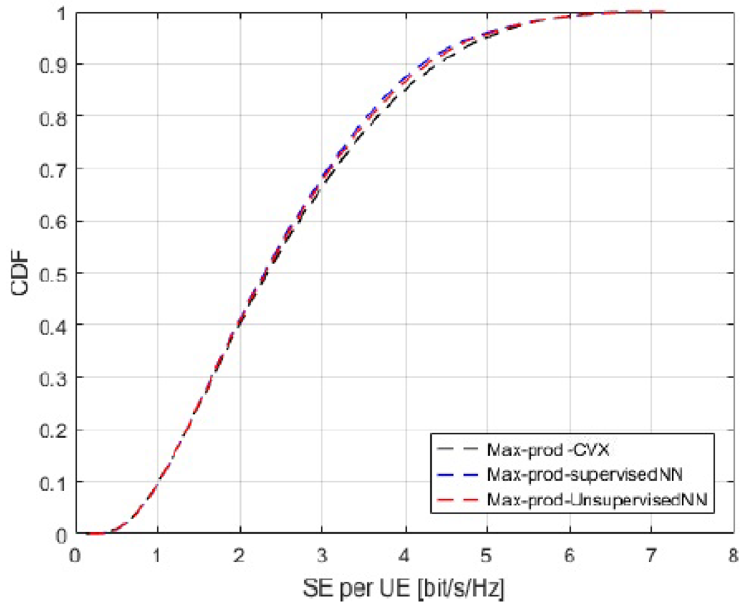

Fig. 4.1: The cumulative distribution function of the spectral efficiency of the downlink of the downlink with the max-product cost function.

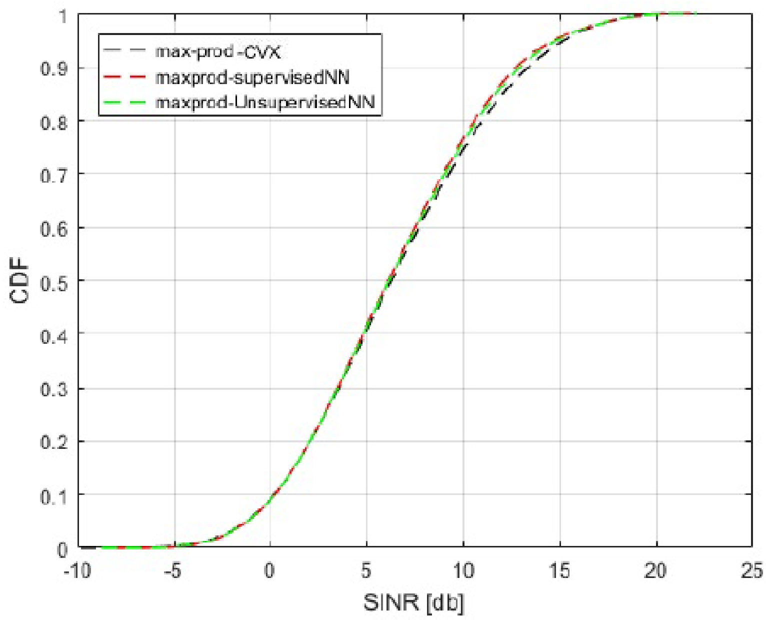

Fig. 4.2: Cumulative distribution function of SINR for the downlink with the max-product cost function is illustrated.

Moreover, Fig. 4.2 depicts the cumulative distribution function in the downlink. Here, it is also observed that the neural network provides results close to the optimal solution. At low SINRs, the results of the optimal solution perfectly match those of the deep neural network, but at higher SINRs, there is a slight discrepancy between the neural network results and the optimal solution due to the use of pre coding MR, which allocates power solely based on desired signal efficiency and does not utilize all user location information, hence resulting in a slight loss compared to the optimal method.

5- Conclusion

In this work, the problem of power allocation in the downlink of a multi-input multi-output massive network with 4 cells and 5 users in each cell is considered. To reduce computational complexity in solving the power allocation problem, the use of a deep neural network is proposed. The training process of this neural network is based on unsupervised learning method, avoiding the complex process of obtaining labels. Initially, the users' positions with their main characteristics of channel propagation and network interference are provided as inputs to the neural network. Then, the neural network performs the training process using gradient descent algorithm and back propagation. Here, unlike supervised training where labeled data is available, a cost function is considered and the Adam optimizer (based on [32]) works towards minimizing this cost function. As demonstrated, the trained neural network has effectively learned how to allocate power to each user in each cell. In fact, it has reduced the solved instances. It can be stated that algorithms based on deep neural networks exhibit a certain amount of efficiency loss compared to the optimal maxprod optimization method, but they have superiority in terms of computational complexity and processing time. Telecommunications resource management, including transmission power for enhancing desired signals and controlling interference signals, is crucial. On the other hand, the number of users in each cell is continuously changing in practice, necessitating quick decision-making and responses in allocating power to users. One proposed solution could be utilizing reinforcement learning tools. In reinforcement learning methods, we do not have explicit instructions; rather, we choose the best course of action through various experiences. In reinforcement learning, the training does not stop; leveraging this very property, network changes can be monitored continuously, and new decisions can be made for emerging situations. Another aspect that could be explored is the use of distributed deep neural networks. In this approach, each cell operates independently, and the neural network input is restricted solely to the connectivity coefficients available to that cell. A drawback of fully connected neural networks is that as the dimensions of optimization vectors increase, the number of neuron connections and training parameters also increase. To address this issue, various other neural network architectures, such as convolutional neural networks (CNNs), can be employed to reduce the number of training parameters in the model.

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