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Towards 6G: Deep Learning in Cell-Free Massive MIMO

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***Abstract*—Massive Multiple-Input-Multiple-Output (MIMO) technology is considered a crucial part of the fifth generation (5G) telecommunications systems. However, moving towards sixth generation (6G) wireless networks, novel solutions have to be incorporated into the current telecommunications' systems. Cell-free Massive MIMO and especially the user-centric approach, seems to be the most promising idea to this direction at this moment. Nevertheless, there are many open issues to be resolved. Deep Learning has been successfully applied to a wide range of problems in many different fields, including wireless communications. In this paper, a review of the state-of-the-art Deep Learning methods applied to Cell-free Massive MIMO communications systems is provided. In addition future research directions are discussed.**

***Index Terms*—6G, Cell-Free Massive MIMO, Deep learning, User-centric Cell-Free Massive MIMO**

I. Introduction

Fifth generation (5G) telecommunications systems are currently commercially deployed in many countries providing to users extremely high data rates, low latency, advanced security and many other appealing amenities. One of the key technologies behind the success of 5G is the Massive Multiple-Input-Multiple-Output (M-MIMO) technology [1].

M-MIMO communications systems consist of a base station (BS) with a large number of antennas $\mathcal{L}$ which simultaneously serves many users $\mathcal{K}$ such that $\mathcal{L} \gg \mathcal{K}$. Some of the advantages of this configuration are the following: *i) high spectrum efficiency*, *ii) energy efficiency* and *high reliability* [1]. M-MIMO operates in a cellular way, similar to the other existing technologies. Despite its appealing characteristics, cellular M-MIMO technology does not reduce large rate variations and inter-cell interference, while challenges in the service quality arise very often [2]. Numerous solutions have been proposed to overcome these issues, however the most promising one at this moment seems to be the Cell-free M-MIMO (CF M-MIMO) scheme [2]- [5]. The core idea behind CF M-MIMO lies on the notion of distributed operation [6]. In CF M-MIMO, $\mathcal{L}$ distributed access points (APs) serve $\mathcal{K}$ users distributed over space such that $\mathcal{L} \gg \mathcal{K}$, and neither cells nor cell-boundaries exist. A central processing unit (CPU) is connected with the APs via the backhaul network, while all users are served through a cooperation between the APs which use time-division duplexing (TDD). The main benefits over the classical cellular technology are: *i) smaller signal to noise ratio (SNR) variations*, *ii) managing interference* and *iii) increased SNR* [2]- [5].

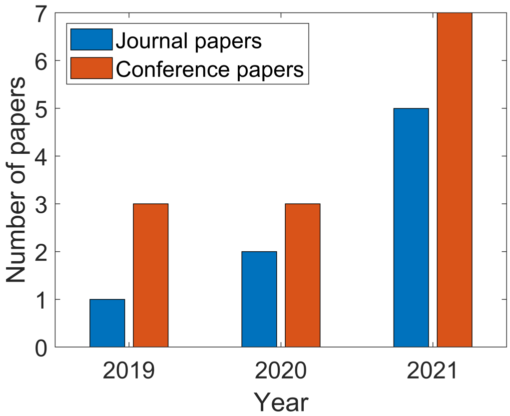

Fig. 1. Number of papers referring to DL applications in CF M-MIMO

Deep Learning (DL) is a subclass of Machine Learning (ML) and recently has emerged as a powerful set of methods, achieving impressive results in many diverse research areas. DL is based on neural networks' architectures, using multiple layers ("deep") of artificial neurons [7]. DL has been utilized also in the field of wireless communications introducing a data driven approach [8], [9]. In this realm, there is a growing research interest in the applications of DL in CF M-MIMO, Fig. 1.

DL may be applied into distinct ML tasks: *i) Supervised Learning (SL)* where a ML algorithm learns a a function that maps an input to an output based on labeled data, *ii) Unsupervised Learning (UL)* where one tries to find underlying patterns or probability distributions in unlabeled datasets, and *iii) Reinforcement Learning (RL)* where a learning agent is able to act within its environment, take actions and learn through trial and error. In practice, however, methods and algorithms from the above categories are combined in order to tackle complex problems [7], [8].

A. Motivation and contributions

The guiding motivation for this research is twofold. On the one hand, moving towards 6G, there is the need to search for novel solutions and test their applicability. On the other hand, the current literature in wireless communications and CF networks is growing rapidly, making it more difficult for researchers to navigate in the field.

The main contributions of this work are as follows

- A thorough review of DL applications on CF M-MIMO networks is conducted. Works that consider CF networks in general were not taken into account
- An introduction to CF M-MIMO and the user-centric approach is provided
- Open challenges and future directions are discussed, providing a framework for further studies

To the best of the authors knowledge, this is the first time that DL methods applied on CF M-MIMO systems is reviewed.

The rest of this paper is structured as follows: In section II the literature review is presented while in section III the basic information about CF M-MIMO communication systems is provided. section IV reviews the various applications of DL in the field of CF M-MIMO. Future research directions are highlighted in Section V, which also concludes this work.

II. Related Work

An extensive presentation of the foundations of user-centric CF M-MIMO is provided in [2]. The applicability of CF M-MIMO to 6G vision is thoroughly discussed in [3], while in [5] for 5G/Beyond 5G networks. In [6] the authors provide a survey of the state-of-the-art literature on CF M-MIMO along with the characteristics of such systems.

To the best of our knowledge this is the first study that discusses explicitly the applications of DL methods to the field of CF M-MIMO.

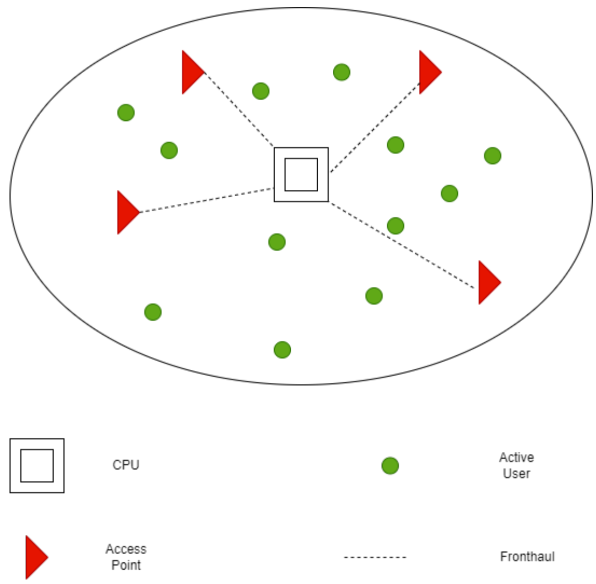

Fig. 2. Cell-Free Network Model

III. Cell-Free M-MIMO

Following [2] CF M-MIMO can be defined as an ultra-dense network where joint transmission and reception are achieved through the cooperating APs which serve the User Equipment (UE). The whole system makes use of the physical layer concepts from the cellular M-MIMO area. More specifically, a CF M-MIMO network is comprised of numerous distributed APs which are connected to a central processing unit (CPU). There is no need for cells and the users are served simultaneously by all APs, (Fig. 2). The motivation behind this idea is to provide an (almost) uniform quality of service in a given space [2].

CF M-MIMO brings a change of paradigm in wireless communications, offering many advantages over the classical 5G cellular M-MIMO systems. In particular, CF M-MIMO technology offers i) smaller SNR variations, ii) managing interference and iii) increased SNR [2] - [5].

Smaller SNR variations are achieved through uniform SNR across the coverage area. By joint transmission from multiple APs inter-cell interference is significantly suppressed. The involvement of APs with weaker channels in the transmission results in an increased SNR, as opposed to the case where only the AP with the best channel is utilized. In addition, having a much larger number of antennas than users, has the effect of creating many spatial degrees of freedom to separate the UEs in space. As a result the transmitted and received signals can be processed using linear methods.

However, CF M-MIMO networks face a serious challenge regarding their practical implementation. Despite its benefits, the technology is not a scalable one, thus making it unsuitable for 6G telecommunications.

TABLE I
DL IN CF M-MIMO

DL Architectures	*Applications*	*Research Paper*
FFNNs	Channel estimation	[16], [18]
	Power allocation	[20], [23]
LSTMs	Power allocation	[21]
CNNs	Channel estimation	[17]
	Power allocation	[19]
Unsupervised Learning	Power allocation	[22]
RL	Power allocation	[24], [25]
	Joint cooperation	[27]

A. *User-centric CF M-MIMO*

As previously stated, the main issue about CF M-MIMO systems is the fact that they are not scalable, thus making them impractical for 6G applications. In order to overcome this problem, User-centric CF M-MIMO has been proposed. In this new setup, a subset of APs is transmitting to the UE. As a result, the fronthaul signaling is reduced, while, at the same time, the performance loss is negligible. Stated differently, User-centric CF M-MIMO makes use of dynamic cooperation clustering, where a subset of APs serves the user k. In [2] one proved that this new configuration is scalable.

Cellular M-MIMO communication systems make use of two emerging phenomena: *i) Channel hardening* and *ii) favorable propagation* [1], which explain the resulting performance gain. Channel hardening explains the situation where a fading channel has almost the same effects with a non-fading channel. Favorable propagation is defined in the case where the vector-valued channels. These two properties are extended in the User-centric CF M-MIMO framework, however a proper mathematical analysis is needed [2].

IV. DEEP LEARNING IN CF M-MIMO

DL has been applied in many different scientific fields achieving impressive results. Recently, researchers in wireless communications have began to train deep neural networks' models in various tasks, including CF M-MIMO. In Table I, the most common used DL architectures applied on CF M-MIMO scenarios are summarized.

A. *DL models*

In this section, the DL models that have been applied in the field of CF M-MIMO are briefly discussed. In this way the non-familiar with the subject reader may refer to this exposition and the corresponding literature.

The basic DL architecture is the Feed-forward Neural Network (FFNN). In this model there exists no feedback loop (or of any other kind) [7], [11]. FFNNs are comprised of many (in principle an unbounded number) layers of artificial neurons and each neuron in one layer is directly connected to the neurons of the following layer.

Convolutional neural networks (CNNs) are a class of DL models that are capable of processing data with a known grid-like topology [7]. Instead of using general matrix multiplication, CNNs make use of the convolution operation in at least one of the model's layers [7]. There are many variants of CNNs that are incredibly successful in numerous tasks such as Computer Vision, Natural Language Processing, time series forecasting etc [12].

Recurrent neural networks (RNNs) are a family of neural networks suitable for processing sequential data [7]. A subset of RNNs which has been successfully applied in many different areas is the Long Short Term Memory networks (LSTM) [13]. In the most general case the LSTM is composed of a cell, an input gate, an output gate and a forget gate [13].

RL is one of the three ML paradigms [7], [14]. As stated before, a learning agent is able to act within its environment, take actions and learn through trial and error. In order to maximize a cumulative reward, the agent tries to find a balance between exploration of ”unknown territory” and exploitation of its ”current knowledge”. Recently the combination of DL architectures with RL (DRL) has provided solutions to many problems [14].

Deep Q-Learning (DQL) is a branch of DRL which is utilized for many tasks. In RL a Q-value is an estimation of how good is it to take the action A at the state S, thus creating a matrix in which the agent can refer to in order to maximize its cumulative reward [14]. The realization that the matrix entries have an importance relative to the other entries, leads us to approximate the matrix values with a deep neural network (DQL).

B. *Channel Estimation*

Channel estimation is the process of characterizing the dynamics of the wireless channel and has a fundamental role in every telecommunications' system including CF M-MIMO [15].

The authors of [16] formulate the concept of channel mapping in space and frequency. Considering a scenario with two set of antennas with different frequency bands, the channels and the frequencies of the first one are mapped to the channels and frequency bands of the other set of antennas. Leveraging the results of their proposed analysis, a FFNN was utilized for channel mapping in a CF M-MIMO model. This DL method managed to reduce both the downlink training/feedback and the fronthaul signaling overhead.

In [17] the authors employ a flexible denoising convolutional neural network (FFDNet) for the task of channel estimation in a CF M-MIMO framework. The results showed that the time spent for the FFDNet training is much less than the time that is needed from the state-of-the-art channel estimators, achieving at the same time similar performance. In order to remove the need for relative reciprocity calibration based on the cooperation of antennas, a cascade of two FFNNs is proposed in [18].

C. *Power Allocation*

The implementation of M-MIMO systems faces the difficulty of resource allocation and power control. This difficulty remains in the CF M-MIMO configurations too. Power allocation refers to the allocation of power to the individual users, in a way to achieve a maximization of the minimum capacity guaranteed to each of them. Since the state of the channel is time dependent, the process of power allocation should be compatible with the channel's dynamics [2], [3].

Exploiting the characteristics of DL techniques one can approximate the power allocation and control problem in a couple of ways. A solution to the sum rate maximization problem is discussed in [19]. The sum rate describes the summation of the achievable rates of multiple concurrent transmissions and the problem of its maximization is a non-convex one. The power allocation problem is converted into a standard geometric program (GP) and the channel statistics is exploited to design the respective power elements. Employing large-scale-fading (LSF) with a CNN allows to determine a mapping from the LSF coefficients and the optimal power through solving the sum rate maximization problem.

The uplink power control is studied in [20]. In a Supervised Learning framework a FFNN is trained to learn the pairs of input-output data. In this particular setting, the optimal solution of the power allocation strategy is the goal of the FFNN's training. In a similar manner the same problem is tackled in [21]. The authors use a LSTM, taking into consideration different scenarios.

A different approach is given in [22]. An Unsupervised Learning setting is established where a FFNN is designed to learn the optimum user power allocations which maximize the minimum user rate. In this way there is no need to know in advance the optimal power allocations. An alternative research direction in problem of downlink power allocation is provided in [23]. First a generalization of maximum ratio precoding is proved and then a NN is trained for every AP to mimic system-wide max-min fairness power allocation. One major benefit is the use of only local information, outperforming the state-of-the-art power allocation algorithms for CF M-MIMO scenarios.

RL has also been employed in CF M-MIMO problems. More specifically, in [24] DQL is utilized. The allocation of the downlink transmission powers in a CF M-MIMO configuration is achieved by making use of a DQN. The sum spectral efficiency optimization problem is discussed. Spectral efficiency refers to the maximum number of bits of data that can be transmitted to a specified number of users per second while maintaining an acceptable quality of service. Exploiting the RL framework of trial-and-error interactions with the environment over time, the DQN is trained taking as input of the long-term fading information and then it outputs the downlink transmission power values.

A similar approach is used in [25]. The proposed DQN and the the deep deterministic policy gradient (DDPG) methods are employed for the task of dynamic power allocation. the goal here is to maximize the sum-spectral efficiency. The numerical results showed a competitive performance with the state-of-the-art weighted minimum mean square error (WMMSE) algorithm.

D. Other applications

Apart from the aforementioned DL applications in CF M-MIMO, there are some insights in other possible use-case scenarios. Considering the case of a large scale CF M-MIMO network, a FFNN is utilized in [26] for pilot assignment. The goal is to maximize the sum spectral efficiency.

Examining the advantages of joint cooperation clustering and content caching in CF M-MIMO, a DRL approach is discussed in [27] demonstrating good energy efficiency performance which does not require prior information.

V. Future directions and Conclusions

It is a common belief among researchers that CF M-MIMO will play a crucial role in the 6G systems' development. As a result, a growing number of papers is being published every year. However, at this point there is no dominant approach to follow for a practical implementation. Although DL methods seem to promise improvements in performance, it is likely that standalone techniques will not be proved sufficient. On the contrary, combined approaches which leverage the individual characteristics of each method are going to dominate the field in the near future.

A great concern is the computational cost of the DL models' training. Reducing the required memory and utilizing results from a "classical" analysis will result in novel solutions. In addition, resources allocation and energy efficiency will be central in the near-future research. At this moment, DL applications focused only on user-centric CF M-MIMO have not been widely considered. In the future it is expected that the results obtained in the classical framework will be expanded to the user-centric approach.

Another factor that will enable future research in this field is the publication of the codes and the rest computational tools that were used along with the published works. Publicly available datasets and simulation codes have helped other fields to grow rapidly. It is inevitable that such a practice will boost the research activity in wireless communications in general.

In this work a comprehensive review of the work around DL methods on CF M-MIMO was provided. More specifically, we focused only on CF M-MIMO systems and not CF networks in general. In particular special focus was given on channel estimation and power allocation. In these three areas DL methods seem to perform better. The different DL models and a review of the state-of-the-art architectures were thoroughly surveyed, while future research directions were highlighted.

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