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THE ROLE OF OPTIMIZATION IN POWER ALLOCATION OF MASSIVE MIMO SYSTEMS

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Abstract— The 5G (fifth generation) network technology aimed to enhance Quality of Service (QoS). Massive multiple-input multiple-output (MIMO) enable the strong 5G experience. In order to deliver the high performance and uniform services to end user the optimization plays an essential role. In this paper, the role of optimization in power allocation of massive MIMO systems has been investigated. Therefore, first an understanding about the massive MIMO and resource allocation has been given, next the need of user scheduling and optimization criteria has been discussed. Further, the paper includes a review of the recent contributions in field of massive MIMO based power allocation problems. During this investigation it is observed that traditionally this problem has been considered as optimization problem and solved by using the improvement on pre-coding and optimization algorithms. On the other hand, recent approaches are recommending the utilization of Deep Learning technology to efficiently and optimally solve the optimization problem. Therefore, the power allocation problem of the massive MIMO has been formulated for solving it with the use of Deep Neural Network. Finally, a complete system architecture has been discussed which will utilized to improve the energy efficiency of massive MIMO operations. Additionally, the conclusion has been made and future extension plan of study has been discussed.
Keywords— Resource Scheduling, Energy Efficiency, Power Allocation, Massive MIMO, Optimization, Deep Learning.

I. INTRODUCTION

Increasing data traffic and subscribers 5G is aimed to develop dense network. The performance demands require new levels of efficiency, and flexibility [1]. Massive multiple-input multiple-output (MIMO) offers larger bandwidth to deliver high quality experience. This technology provides uniform service quality in high-mobility environments [2]. The key concept is to equip Base Stations (BS) with arrays of many antennas, which are used to serve many users, in the same time-frequency resource. The “massive” refer to the number of antennas [3]. It operates in TDD mode and downlink beam-forming exploits the uplink-downlink reciprocity of radio propagation. The BS array uses channel estimates uplink pilots transmitted to learn the channel. This makes Massive MIMO scalable with respect to the number of antennas.

BS operates separately, with no sharing of payload or channel state. Wireless systems require understanding of design principles and control system to manage resources. Resource allocation policies lie at the heart of wireless networks. The aim is guaranteeing the Quality of Service (QoS), with ensuring efficient and optimized operation [4]. Resource allocation may include network features, like scheduling, transmission rate control, power control, bandwidth reservation, call admission control, transmitter assignment, and handover. A resource allocation policy is defined by [5]:

i) A multiple access technique and scheduling distributed resources among users to satisfy QoS.
ii) A signaling strategy to simultaneous transmission of data streams to the scheduled users;
iii) Rate allocation and power control that guarantee QoS and harness interference

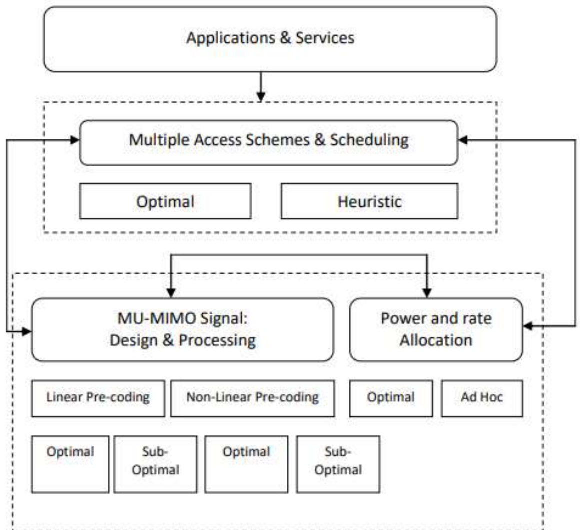

Fig. 1 Components of resource allocation policy in MU-MIMO

Fig. 1 illustrates components and connection between them. It highlights the resource allocation strategy performed. In this section provide the overview of MIMO technology and next section discusses different resource allocation techniques.

II. BACKGROUND

The multiple access schemes can be classified as orthogonal or non-orthogonal. The scheme assigns radio resources, e.g., code, sub-carrier, or time slot, to a user per transmission. The key property of orthogonal multiple access schemes are reliability. The resource allocation policy can optimize with reasonable performance metrics, such as throughput, fairness, and QoS [6]. The number of user is limited by the number of radio resources. In non-orthogonal multiple access, a set of users superimpose their transmissions over the same resource, and interfere with each other [7].

In this scheme the co-resource interference can be mitigated by signal processing and transmission techniques. Such techniques exploit different resources, such as power, code, or spatial domain, and a combination to cope with high data rate requirements and efficiency. In MIMO a multi-antenna BS or access point (AP) transmits one or more data streams to one or more users, and provide high throughput [8]. Resource allocation is challenging in wireless communication due to the medium variability and channel randomness, which renders the performance location-dependent and time-varying. By spatial degrees of freedom (DoF) of multiple antennas we can avoid resource wastage. In Massive MIMO few hundreds of antennas are employed. It has been identified as interface technologies to address the massive capacity [9].

The downlink transmission is challenging because the geographic location of the receivers is random and joint detection cannot be performed. The aim is to convey data to a set of users. However, determining set of users is challenging, which depends on resource allocation strategy, e.g., individual QoS, signaling schemes, rate allocation and power control [10]. It allows signal processing techniques to enhance performance by using a multi-dimensional resource pool. This pool is composed of resources, e.g., signal spaces, transmission powers, time slots, sub-carriers, codes, and users. Efficient allocation for a large set of resources implies a trade-off between optimality and feasibility. The optimality can be reached by solving optimization problems over a set of variables. Feasibility implies suboptimal resource allocation takes place by relaxing and reformulating optimization problems [11].

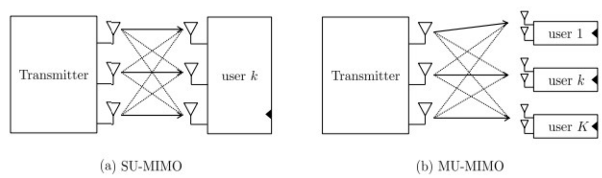

Figure 2 (a) Single-user (SU) and (b) Multi-user (MU) MIMO modes

A. The need of User Scheduling

In MU-MIMO performance depends on how efficiently the resource allocation algorithms manage the hyper-dimensional pool. The resources include carriers, time slots, codes, power, antennas, users, etc. Consider a system with a transmitter with M antennas, and $K' = \{1, 2, 3, \dots, K\}$ be the set of users, as given in Figure 2. To determine the objectives of scheduling the following definitions have been used [12]:

1. **QoS:** It defines a set of network-/user-based performance targets like peak rates, error rates, delays, or stability that can be measured, improved, and guaranteed.
2. **User scheduling.** A set of radio resources like time slot, codes, sub-channels, powers, etc. has been assigned to users, $K \subseteq K'$, so performance is optimized to power and QoS.

Consider that each user $k \in K'$, is equipped with N_k antennas. Than transmit antennas ($M < \sum_k N_k$),one can solve a selection problem to achieve MUDiv gains in fading channels. The task in resource management is to select a subset of user $K \subseteq K'$, and assign resource to it. Let a single-transmitter and user scheduling problem for a single resource as follows:

$$maximize \sum_{k=1}^{K} \varepsilon_{\pi(k)} U_{\pi(k)}$$

The aim is to maximize sum of the utility functions $U_{\pi(k)}, \forall k$, which depends on: multiuser MIMO channel H_k, the allocated power p_k, data queues q_k, and the encoding order $\pi(\cdot)$. The QoS requirements can be included as $U_{\pi(k)}$, as individual weights [3].

$$subject\ to \sum_{k=1}^{K} \varepsilon_k p_k \leq P$$

$$0 \leq \varepsilon_k p_k \leq P_k \quad \forall \mathrm{k} \in \mathrm{K}'$$

$$\sum_{k=1}^{K} \varepsilon_k \leq c_p$$

$$\varepsilon_k \in \{0,1\} \quad \forall \mathrm{k} \in \mathrm{K}'$$

The equations define total and individual power constraints, which are set according to the scenario $\varepsilon_{\pi(k)}$, which is equal to 1 if the $\pi(k)^{\text{th}}$ user is scheduled otherwise 0. The set of selected user is given by:

$$K = \{k \in K' : \varepsilon_k = 1\}$$

The system operates in MU-MIMO mode if

$$1 < |K| \leq c_p$$

Where c_p is the maximum number of user streams, to send over M antennas. If the solution exists for $|K| = 1$ the system operates in SU-MIMO mode.

For example optimization can be formulated to attain high rate, and reliability gains. The type of signaling and coding applied to the data, the number of users with optimal power is upper bounded as [3]:

$$|K| \leq c_p \leq M^2$$

The gain can be scaled up to:

$$|K| \leq M$$

The users are fixed and chosen to construct K, the utility functions change according to the channel conditions and the resource allocation. Finding optimal set K, is a combinatorial problem due to ε_k, and encoding $\pi(\cdot)$. Moreover, need to deal with non-convex functions on the multiple parameters, e.g. K, M, N_k, etc. The feasibility relies on the conditions and processing. The scheduling problem can be solved by exhaustively searching (ExS) over all possible set. The computational complexity of ExS is high, even for small K. It can be modified to include properties, like multiple carriers for OFDMA or codes for CDMA.

B. Optimization Criteria

It finds the optimal resource allocation, and can be classified in two groups:

a. **PHY layer based criteria** is an objective function $U(\cdot)$. The channel is the only input to the allocation algorithms.
b. **Cross layer based criteria**, is optimization of $U(\cdot)$, to consider QoS requirements and channel information.

Additionally, there are two concepts in multiuser system optimization:

A. **Resource allocation feasibility**: For a set of users K, a resource allocation is feasible if it fulfils all constraints (e.g. power and QoS), with pre-coding, power control, or a combination.
B. **Feasible set of users**: The set of all competing users K', where $K \subseteq K'$, is called feasible if pre-coding weights and powers, $\forall k \in K$, such that $U(\cdot)$ has a solution meeting QoS and power constraints.

In order to understand the recently developed techniques and methods which are utilizing the scheduling is discussed in next section.

III. POWER ALLOCATION OF MASSIVE MIMO SYSTEMS

This section offers study of the noteworthy contributions for power scheduling and optimization techniques. The aim is to identify the optimal power and user combination to serve better with compromising the QoS requirement. However, a significant number of articles have been collected by only more relevant work has been discussed in this section.

A. Abbreviations

The frequently used terminology and abbreviations are reported in table 1.

Table 1 abbreviations

Abbreviations	**Full form**
CSI	Channel state information
DL	Downlink
DNN	Deep neural network
DoAs/DoDs	Directions of Arrival/Departure
EELCA	EE low-complexity algorithm
ESR	Ergodic secrecy rate
GP	Geometric programming
JRP	Joint relay selection and power allocation
LS	Least squares
Max-Min MCA-RZF	Max-min multi-cell aware regularized zero-forcing
mmWave	millimeter wave
MSE	mean square error

OMA	orthogonal multiple access
PA	power allocation
RAS	receive antenna selection
SE	Spectral Efficiency
SIC	successive interference cancellation
SINR	signal-to-interference plus noise ratio
ZFBF	zero forcing beam-forming

B. Recently used resource scheduling

T. V. Chien et al [13] considers pilot design to mitigate pilot contamination and provide good service. In place of pilot design, they express the pilot signals using a pilot basis and treat the power coefficients as optimization variables. They compute a lower bound on uplink capacity for Rayleigh fading channels with maximum ratio detection. Then formulate the max-min fairness problem under power budget constraints, with pilot signals and data powers as optimization variables. Then obtain a local optimum with polynomial complexity. It serves as a benchmark for pilot design.

L. Sanguinetti et al [14] advocates the use of deep learning to perform max-min and max-prod power allocation in the downlink. A deep neural network is trained to learn the map between the positions of user equipments (UEs) and optimal power allocation policies, and then used to predict the power allocation profiles for a set of UEs'. The deep learning improves complexity-performance trade-off of power allocation, compared to traditional methods.

A. Salh et al [15] aims to control power allocation as a metric to maximize energy efficiency (EE). The performance was evaluated for circuit power consumption. The aims to maximize the non-convex EE in a DL using EELCA for optimal power allocation using Newton's methods and joint user's association based on Lagrange's decomposition. An optimal power allocation to decrease complexity of the power subject to both the maximum power and minimum data rate was derived. Then, solve the optimal power allocation based on differentiating instantaneous power allocation.

An increased number of antenna arrays consume more power. ***A. Salh et al [16]*** investigated how to obtain the maximal data rate by deriving the optimal number of RF chains. To mitigate inter-user-interference and to compute power allocation, they used the pre-coding scheme ZFBF. The data rate is increased by choosing of the maximum power in relation to the antenna selection. The transmit power allocation allows the use of less number of RF chains which provides the maximum data rate.

J. Xu et al [17] proposes a deep learning based pilot design scheme to minimize the sum MSE of channel estimation. The pilot signal of each user is expressed as a weighted superposition of ortho-normal pilot sequence, where power assigned to each pilot sequence is corresponding weight. A DNN is designed to optimize power allocated, which takes the channel large-scale fading coefficients. The loss function is defined as MSE, and use unsupervised learning to train DNN.

W. Hao et al [18] investigate EE problem in mmWave massive MIMO system with NOMA. Multiple-user clusters are formed according to channel correlation and gain difference. They propose a hybrid analog/digital pre-coding for the low RF chains structure. On this basis, formulate a power allocation problem to maximize the EE under users' QoS requirements and power. Results show that the NOMA achieves superior EE.

Existing algorithms are limited due to full channel knowledge and high complexity. ***M. Shehata et al [19]*** introduce a low complexity, angular based beam-forming and power allocation that requires the knowledge of the DoAs/DoDs. Propagation conditions are driven by the geometrical structure of the channel, this method relies on the estimation of the leakage caused by each UE on other UEs. The results, enhance the network SE with acceptable data rates.

A. Kuhestani et al [20], JRP is proposed to enhance security. For maximizing the instantaneous secrecy rate, they derive a closed-form solution for optimal power allocation and propose a relay selection criterion. The closed-form expression is derived for the ESR and secrecy outage probability as security metrics and closed-form expression for reliability. They characterize the high signal-to-noise ratio slope and power offset to highlight the impacts.

M. Rihan et al [21] propose a joint IA and PA system. Approaches for applying IA in downlink will be addressed with a PA technique that exploits the properties of NOMA-based systems. This system aims to maximize the sum-rate through combining IA with PA. First, grouping the users into clusters then sum-rate maximization is carried out under power budget, QoS, and SICs constraints. It uses power domain multiplexing to share the data. The algorithms are compared with OMA-based and NOMA-based systems. Simulations verify that system can improve the performance of NOMA-based systems in terms of sum-rate.

S. Chakraborty et al [22] first generalize method of pre-coding, and then train a neural network to perform the power allocation with reduced complexity. Finally, train a neural network per AP to mimic system-wide max-min fairness power allocation. By learning the structure of the propagation environment, this method outperforms.

M. Bashar et al [23] consider max-min SINR problem for the uplink transmission. Assuming that, the users exploit the knowledge of the channel, thus derive a closed-form expression for uplink rate. They enhance user fairness by power allocation and choice of receiver coefficients, where the minimum uplink rate of the users is maximized with transmission power. Based on expression, design the optimal receiver coefficients and power allocations. They develop an algorithm for optimal receiver coefficient and user power allocations. The receiver coefficients design for fixed user power allocation as generalized using GP.

H. T. Dao et al [24] consider pilot and data power allocation to maximize sum SE is forming a maximization problem as objective function. Improving channel estimation quality improves the sum SE. Thus propose a disjoint pilot and data power allocation based on sum NMSE channel estimation minimization and data powers are optimized based on sum SE maximization. They consider LS and MMSE estimation. First, minimize the summation of NMSE under maximum pilot power per user and Minimization for MMSE to find the local optimum point. Next, improve sum SE by maximization problem with data powers. They derive a lower bound and maximize this bound.

W. A. A. Hussaibi et al [25], approach of NOMA with RAS for uplink channel to increase the UEs and sum rate capacity with user-fairness and low complexity. It is designed from two clusters, based on number of RF chains and channel conditions, power-domain NOMA for signal transmission. They derive sum rate and capacity region expressions with RAS over Rayleigh fading channels. Then, optimal and efficient dynamic user clustering, RAS, and power allocation algorithms are proposed.

S. Zarei et al [26] propose a Max-Min MCA-RZF pre-coding and power allocation. A correlated channel model is used, and CSI acquisition model includes the effects of estimation errors and pilot contamination. They use results from random matrix theory to derive deterministic equivalents for the Max-Min power allocation. The results show that pre-coder achieves a higher network wide minimum rate than MCA-RZF and RZF pre-coders.

To solve max–min non-convex problem, ***M. Bashar et al [27]*** decouple the original problem into two sub-problems, receiver filter coefficient and power allocation. The receiver filter coefficient is formulated as a generalized Eigen-value, whereas the geometric programming is used to solve the user power allocation problem. Based on these problems, an algorithm is proposed. This algorithm obtains an optimum solution through establishing an uplink–downlink duality. They present a scheme which provides efficient and global maximize the minimum uplink user rate. The results demonstrate that the scheme outperforms.

V. REVIEW SUMMARY

According to our understanding, we can explain the scheduling in massive MIMO systems in simple words. Basically due to need of QoS requirements we need to enable multiple steams to each user. But, to control the energy efficiency and other QoS requirements it is required to estimate the relevant resources. The mapping between the user requirements and available resources are scheduled a service profile. The main problem is to find the optimal mapping and locating a profile for a selected group of users for offering services.

Table 2 Review summary

Ref	Problem Domain	Solution	Results
[13]	Pilot design to mitigate pilot contamination and good service	In place of pilot design, the pilot signals using a pilot basis and treat power coefficients as optimization.	Framework serves as a benchmark for pilot design. This algorithm is close to the optimal solution.

[14]	Advocate use of deep learning to perform power allocation.	DNN learn map between UE positions and allocation policies, then predict profiles for UEs'.	Does not require computation of any average, and guarantee near-optimal performance.
[15]	Singular value decomposition is essential for high performance signal processing	control power allocation as a metric that maximizes EE	EELCA with total transmitted PA provided maximum EE. Cost of circuit power usage increased due to the loss of RF chains.
[16]	Increased number of antenna arrays consume more power due to number of RF chains	How to obtain the maximal data rate by deriving the optimal number of RF chains from large number of antenna arrays.	The transmit PA allows use of less number of RF chains which provides the maximum data rate depending on the optimal RF chain.
[17]	minimize sum MSE of channel estimation	A multi-layer fully connected DNN is designed	Results show that the scheme achieves better sum MSE than other methods.
[18]	EE problem in a mmWave massive MIMO system	A hybrid analog/digital pre-coding scheme for low RF chains structure. Formulate a power allocation to maximize the EE under QoS need and per-cluster power.	Results show that the NOMA achieves superior EE than conventional OMA.
[19]	full channel knowledge and high complexity	A low complexity, angular based beam-forming and power allocation that requires the knowledge of DoAs/DoDs.	Prove this approach, practically plausible; enhance network Spectral Efficiency (SE) with adequate data rates.
[20]	protect data confidentially while relying on un-trusted relays to improve security and reliability	maximizing the instantaneous secrecy rate, they derive a closed-form solution for optimal power allocation and propose a relay selection criterion	ESR of the JRP for NCE and CE cases is increased
[21]	maximize the sum-rate through combining IA with PA	Group users into clusters then sum-rate maximization have done. It uses power domain	Algorithms are compared with OMA-based MU-MIMO and NOMA-based systems. Verify that system

		multiplexing within cluster to share data without interference.	can improve performance in terms of sum-rate.
[22]	Downlink power allocation	Generalize method of pre-coding, and then train a neural network to perform the power allocation	this method outperforms
[23]	consider max-min SINR problem	Derive a closed-form expression for uplink rate. Enhance user fairness by power allocation and receiver coefficients, where uplink rate is maximized with power.	Enhance user fairness
[24]	Consider pilot and data power allocation.	(1) Minimize summation of NMSE under maximum pilot power and Minimization of MMSE to find local optimum point. (2) improve sum SE by maximization of data powers.	Pilot powers are optimized based on the sum normalized mean squared error channel estimation minimization and data powers are optimized based on sum SE maximization.
[25]	Increase number of UE and sum rate capacity	Designed by two MUMIMO clusters, based on the number of RF chains and channel conditions.	increase in connectivity, up to two-fold for the number of RFCs, and sum rate capacity
[26]	Max-min multi-cell aware regularized zero-forcing	A correlated channel model is considered, and CSI acquisition model	pre-coder achieves a higher minimum rate than MCA-RZF and RZF pre-coders
[27]	Max–min non-convex problem	receiver filter coefficient and power allocation	uplink–downlink duality, minimum uplink user rate

According to the studied literature the authors are either considering uplink or downlink based scenarios for simulation and experiments. There are very fewer techniques are experimented with both the scenarios uplink and downlink. A highlight of the studied articles is given in table 2. The table highlights the problem which is considered on the article, the used solution and the obtained influence on the performance parameters. In these articles, the methods are formulated as optimization problems and the QoS variables are used for optimizations and find appropriate mapping. In this context, most of the authors are following the traditional ways problem.

But, in article [14], [19] and [22] the authors are utilizing the different way to handle the scheduling problem. Additionally, the article [14] and [22] they recommend to utilize the deep learning technique to solve the min-max optimization problem.

In [14] a deep learning based pilot design scheme is described. The aim is to minimize the sum MSE of channel estimation. The pilot signal of each user is expressed as a weight of orthonormal pilot sequence basis, where the power assigned to each pilot sequence is the corresponding weight. A multi-layer DNN is designed to optimize the power allocated to each pilot sequence. They use unsupervised learning to train the DNN.

Downlink power allocation is important to determine which APs transmit to which users and at what power. Previous works shows how to perform max-min fairness power allocation. In [22] first generalize this method to arbitrary pre-coding, and then train a neural network to perform same power allocation and reduce complexity. Finally, they train a neural network per AP to mimic system-wide max-min fairness power allocation using local information. By learning the structure of the local environment, this method outperforms. In this article the aim is to demonstrate large-scale fading information is sufficient for computing the optimal powers. In contrast to the traditional optimization problem by solving below equation:

$$\underset{\{\mu_{kl}:\forall k,l\},c}{\text{maximize}} \quad c$$

Subjected to:

$$\sqrt{\frac{1}{s}c_k^T\mu_k} > \left\| B_k \left[\frac{\mu}{\sqrt{\sigma^2}} \right] \right\|, \; k = 1, \dots, k$$

$$\sum_{i=1}^{K} \mu_{il}^2 \leq cP_{max}^{dl}, \quad l = 1, \dots, L$$

Where$c_k = [|a_{k1}| \dots |a_{kL}|]^T \in \mathrm{C}^{L\times 1}$, and $\mu_k = [\mu_{k1} \dots \mu_{kL}]^T \in \mathrm{C}^{L\times 1}$, $B_k = diag\,\sqrt{b_{k11}} \dots \sqrt{b_{kKL}1} \in \mathrm{C}^{(KL+1)\times(KL+1)}$and $\mu = [\mu_1^T \dots \mu_K^T]^T \in \mathrm{C}^{KL\times 1}$.

That requires knowledge of $\{a_{kl}\}$ and $\{b_{kil}\}$. These variables are defined by:

$$a_{kl} = E\{h_{kl}^H D_{kl} w_{kl}\}$$

$$b_{kil} = E\{|h_{kl}^H D_{kl} w_{kl}|^2\} - \begin{cases} 0 & for\ i \neq k \\ |a_{kl}|^2 & for\ i = k \end{cases}$$

Authors are recommending the use UEs' large-scale fading coefficients $\{\beta_{kl}\}$ to perform power allocation. Therefore, for a given location of APs, the problem is to learn the unknown mapping between $\{\beta_{kl}\}$ and the optimal square-roots of the transmit powers $\{\mu_{kl}^*\}$. This is achieved using DNN's universal function approximators. The neural network is applied here to $\hat{\mu}_{kl}$ of $\{\mu_{kl}^*\}$. The problem is to train weights and biases of the NN so that it can learn $\{\mu_{kl}^*\}$. They consider two DNNs with both MR and RZF pre-coding. First is centralized DNN with input the large-scale fading coefficients $\{\beta_{kl}: \forall k, l\}$ and provides network-wide square-roots of the powers $\{\hat{\mu}_{kl}: \forall k, l\}$. Second is decentralized because it operates on a per-AP. The DNN of AP l receives as input only the locally available coefficients $\{\beta_{kl}: \forall k\}$ and aims to learn the local estimate $\{\hat{\mu}_{kl}: \forall k\}$ of optimal powers. The advantage of the decentralized DNN is that no exchange of large-scale fading coefficients among APs is required.

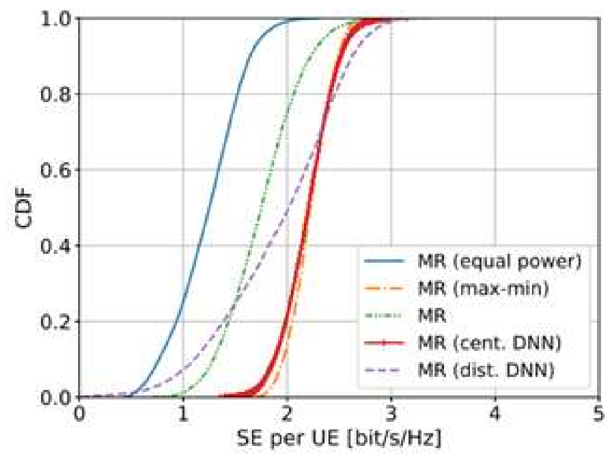

Figure 3 CDF of DL SE per UE with MR

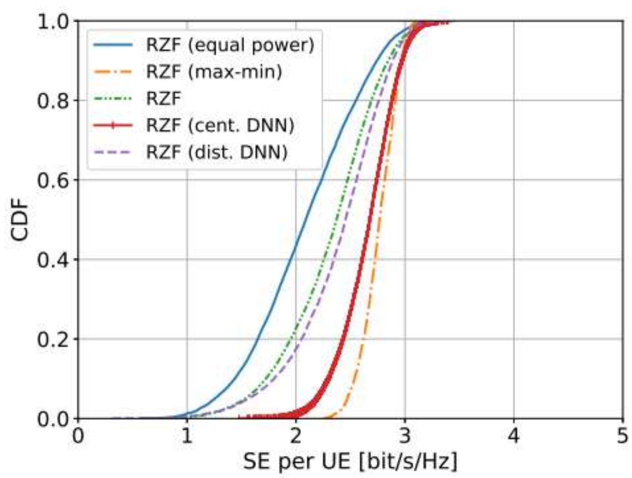

Figure 4 CDF of DL SE per UE with RZF

Figure 3 shows the cumulative distribution function (CDF) with MR pre-coding and Figure 4 shows CDF of downlink SE per user with RZF pre-coding. The centralized DNN follows the performance achieved with the max-min algorithm. The distributed DNN outperforms for 80% of the UEs, but lower SE for the 20% most unfortunate users. The DNN based power allocation is that it learns the propagation environment of the network so that every AP can apply a locally optimized power allocation. However, there is a gap between distributed and centralized methods. For 40% users, the centralized DNN power allocation closely approximates the conventional max-min fairness algorithm. It achieves 42% higher average SE.

VI. CONCLUSIONS

The balance between quality of service requirement and resource utilization is the key subject of optimization and scheduling techniques. In massive MIMO concept, the number of user's equipments is dynamic and resource availability is also dynamic in nature. In addition, the demand of data upload and download is also dynamic in nature. Therefore, due to dynamicity maintaining balance between resource demand and supply in power allocation strategy building is an essential concept. In this paper, the massive MIMO has been investigated in order to achieve the optimal scheduling of power. In this context, first the concept of optimization and their use in massive MIMO communication has been discussed. Then, a review of recent techniques for enhancing the scheduling techniques has been studied.

During investigation we have located three unique methods for MIMO power allocation. Among two of them are utilizing the deep learning technique for downlink power allocation. Both the techniques are utilizing the unsupervised method of utilizing the deep learning algorithms. Using these papers we have motivated to propose the following task for our future work:

1. Implement a simulation of massive MIMO power allocation and scheduling
2. The scheduling technique utilize a meta heuristic algorithm for obtaining the appropriate mapping of user mobile and resources
3. Implement a service profile based resource assignment system for improving the quality of service and power management

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