A Machine Learning Adaptive Beamforming Framework for 5G Millimeter Wave Massive MIMO Multicellular Networks

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ABSTRACT The goal of this paper is to evaluate the performance of an adaptive beamforming approach in fifth-generation millimeter-wave multicellular networks, where massive multiple-input multiple-output configurations are employed in all active base stations of the considered orientations. In this context, beamforming is performed with the help of a predefined set of configurations that can deal with various traffic scenarios by properly generating highly directional beams on demand. In parallel, a machine learning (ML) beamforming approach based on the k-nearest neighbors (k-NN) approximation has been considered as well, which is trained in order to generate the appropriate beamforming configurations according to the spatial distribution of throughput demand. Performance is evaluated statistically, via a developed system level simulator that executes Monte Carlo simulations in parallel. Results indicate that the achievable spectral efficiency (SE) and energy efficiency (EE) values are aligned with other state of the art approaches, with reduced hardware and algorithmic complexity, since per user beamforming calculations are omitted. In particular, considering a two-tier cellular orientation, then in the non-ML approach EE and SE can reach up to 5 Mbits/J and 36 bps/Hz, respectively. Both metrics attain the aforementioned values when the ML-assisted beamforming framework is considered. However, beamforming complexity is further reduced, since the ML approach provides a direct mapping among the considered throughput demand and appropriate beamforming configuration.

INDEX TERMS 5G, massive MIMO, millimeter-wave transmission, machine learning, adaptive beamforming.

I. INTRODUCTION

The massive deployment of fifth-generation (5G) broadband wireless cellular networks has enabled the transition towards advanced features and services, such as ultra-reliable low latency communications (URLLC), enhanced mobile broadband as well as massive machine type communications (mMTC) [1], [2]. In this context, various novel technologies have been developed in the physical layer, such as non-orthogonal multiple access (NOMA) [3], that can leverage spectral efficiency (SE), millimeter wave (mmWave) transmission [4], as well as massive multiple input multiple output (m-MIMO) configurations [5]. In the latter case, a very large number of transmitting antennas is deployed over various access points (APs) of the wireless orientation in order to support high data rate transmission in multiple mobile stations (MSs) as well as seamless end-to-end connectivity. Hence, a holistic network redesign is required that will be able not only to support the coexistence of various novel technologies but also the integration of heterogeneous hardware components and services.

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Over the last years, the concept of ultra-dense networking (UDN) has emerged as a promising solution that can improve both SE and energy efficiency (EE) over small geographical areas [6], [7]. However, the deployment of a large number of APs may not only significantly increase signaling burden, since channel state information (CSI) is required, but leverage the pilot contamination effect as well. The latter term refers to the reuse of pilot signals among adjacent cells for channel estimation [8]. It becomes apparent from the above that the full exploitation of m-MIMO configurations with reduced hardware and algorithmic complexity requires a multi-user (MU) beamforming approach that can deal with various quality of service (QoS) requirements and system constraints.

Machine learning (ML) algorithms can deal with a variety of problems related to process optimization, triggering a vast amount of research activities in this area. To this end, data collected directly from the network which are related to one or more key performance indicators (KPIs) are properly processed in order to define the most appropriate radio resource management (RRM) strategy for an upcoming time slot [9]. In this context, the most important ML approaches are supervised learning (SL), unsupervised learning (UL) as well as deep reinforcement learning (DRL). In the first case, training is performed according to a well-known predefined set of desired outputs. In the second case, the goal is the extraction of potential patterns from unlabeled data. Finally, in the last case, the best policies are defined dynamically via mobile agents that interact with the wireless environment [10].

In this work, the performance of an adaptive beamforming approach has been evaluated, when deployed in 5G multi-cellular MU wireless orientations. To this end, the developed m-MIMO configuration is based on a low cost square array of rounded crossed bowtie radiating elements operating at 28 GHz. The proposed framework has been leveraged by the deployment of an SL approach based on the k-nearest neighbors (k-NN) approximation. As it will be described in detail in the results section, the developed approach can improve both SE and EE, with reduced hardware and algorithmic complexity.

A. RELATED WORK

Over the last years, various research activities have focused on EE-SE maximization in m-MIMO configurations, under various constraints. In [11], the achievable SE of MU m-MIMO systems was evaluated, when the base station (BS) has perfect CSI. In this context, various uniform linear array antennas were considered. In [12], a low-complexity sub-optimal two-layer waterfilling-structured power allocation algorithm was proposed and evaluated, for resource efficiency optimization. The latter term is defined as a weighted sum of EE and SE. According to the presented results, the proposed approach can significantly improve resource efficiency, when statistical CSI is available at BSs. In [13], the sum SE and total EE of a cell-free m-MIMO system operating over correlated Rician fading channels was investigated. To this end, two successive approximation algorithms were developed to improve the aforementioned metrics, by optimizing the power control coefficients of downlink data and pilot signals. In [14], the combined impacts of quantized phase shifters, channel non-reciprocity and channel estimation errors on the achievable SE of an m-MIMO system were investigated. In this context, closed-form expressions were derived. In [15], a resource allocation method was proposed in order to maximize the SE of a single-cell m-MIMO time-division duplex (TDD) system. The presented results indicate that SE can be significantly improved at the high signal to noise region by allocating more power to data symbols for a given total power budget. According to [16], the usage of low-resolution analog-to-digital converters at the receiver can greatly reduce hardware costs and circuit complexity leading to a further improvement of EE in m-MIMO systems. In [17], the achievable SE of multi-antenna users has been investigated, in cell free m-MIMO environments. To this end, two transmission protocols were considered, depending on the usage of pilot signals. Results reveal that the system can achieve the sub-optimal performance regardless of the number of users in the system. In [18], the authors have studied the SE of frequency selective cell free m-MIMO systems with phase noise, considering two low complexity receivers. In [19], there was a double design goal. The first one was the maximization of EE in uplink and downlink. The second one was the optimization of the total number of antennas, the number of active users as well as the total downlink transmission power. The proposed approach provides fast convergence and outperforms other existing schemes which do not consider the hardware impairments and/or the CSI error. In [20], EE maximization was studied when simultaneous wireless information and power transfer was considered over m-MIMO systems. In this context, the authors have proposed an alternative and low-complexity iterative strategy to overcome the non-linearity and nonconvex characteristic of the original EE maximization problem. The work in [21], elaborated on EE maximization when compact planar arrays were deployed in BSs. Numerical results indicate that when the phenomenon of mutual coupling is taken into consideration, the proposed approach outperforms other conventional approaches related to EE optimization. In [22], the authors investigated appropriate user association and power allocation strategies in multi-connectivity enabled mmWave networks. In this context, the goal was to optimize overall system EE and balance user rate among all users and traffic load among all BSs. The results showed that multi-connectivity technology can improve the overall system EE.

The employment of ML approaches in order to improve various performance metrics of m-MIMO configurations has attracted scientific interest during the last decade as well. To this end, in [23] an unsupervised deep learning method was proposed to design the hybrid beamforming in m-MIMO systems. According to the presented results, the proposed method can increase SE, by using partial CSI feedback. Reference [24] presented a deep learning approach for downlink precoder design in m-MIMO systems by making use of
channel estimates and statistical parameters of channel estimation error. In this context, near-optimal performance can be achieved with low computational complexity. In [25] a deep Q-network (DQN) based power control scheme was proposed for improving the system-level EE of two-tier 5G heterogeneous orientations. Results show that the multi-agent DQN approach can significantly improve SE, since the decentralized learning supports low-dimensional agents to be coordinated with each other through global rewards. In [26], an RL approach has been considered, for EE maximization in 5G m-MIMO orientations. The proposed algorithm maximized EE in an independent way for every set of MSs’ positions. Afterwards, the process of learning is accelerated by exploiting similarities in the obtained data. In [27], the authors investigated the joint pilot and data power control for the sum SE maximization in uplink m-MIMO systems via deep learning with a convolutional neural network. The main results of this work indicate that sum SE loss is limited to 2% for a topology with nine cells. In [28], the authors proposed a two-layer based joint channel prediction and beamforming algorithm based on RL. According to the presented approach, at the first step a learning agent imports the received pilots into the prediction network in order to acquire CSI estimation. Afterwards, the second stage can autonomously learn the beamforming policy with the objective of maximizing the transmission sum rate. The simulations verified that the proposed algorithms could always get converged and stable after certain training steps. In [29], a MIMO broadcasting channel has been considered, where the goal is to maximize the sum-rate of all users by jointly optimizing the transmitter and receivers under the total power constraint. To this end, an unsupervised learning strategy has been developed, which can significantly reduce inter-user interference. Finally, in [30], two unsupervised deep neural networks (DNN) architectures were proposed and evaluated (fully and partially distributed), that can perform decentralized coordinated beamforming with zero or limited communication overhead between APs in cell-free m-MIMO systems. Simulation results indicate that near-optimal performance can be achieved with reduced computational complexity and signaling burden.

B. CONTRIBUTIONS

In all the aforementioned studies, either limited network topologies have been considered (i.e., single-cell scenarios) or limited number of active users. Therefore, the potential benefits of m-MIMO configurations in large scale MU environments need to be evaluated, especially in the presence of additional novel technologies. This is also the case for ML algorithms, where their performance evaluation in m-MIMO mmWave configurations is again limited in topologies with moderate number of users. The goal of the current study is the performance evaluation of a proposed adaptive beamforming approach for SE and EE maximization in multicellular-MU m-MIMO orientations. Overall, the key novel points of our work can be summarized as follows:

- An efficient adaptive beamforming framework that improves EE and SE with reduced hardware and algorithmic complexity, since beamforming is performed with the help of a predefined set of configurations that can deal with various traffic scenarios by properly generating highly directional beams on demand.
- Leveraging the aforementioned framework with the help of an ML-assisted beamforming approach based on the $k$-NN approximation.
- Performance evaluation of the considered algorithms for various KPIs when employed in 5G mmWave multicellular orientations, where the latest 3GPP channel model has been incorporated [31]. This is made feasible with the help of a developed system level simulator, that executes Monte Carlo (MC) simulations in parallel.
- Electromagnetic analysis focused on the directivity enhancement of the proposed adaptive antenna array configuration.

The study presented in this paper is actually a continuation of the work initially presented in [32]. The current version provides a more detailed analysis of the considered wireless orientation and the proposed antenna design. Moreover, the adaptive beamforming approach has been updated as well, in order to deal with mixed traffic scenarios. In the same context, extended simulations that cover various throughput demands in non-uniform traffic scenarios are presented.

The $k$-NN approximation has been considered in similar problems related to KPI optimization for wireless networks as well. For example, in [33], a $k$-NN SL model has been used in an adaptive modulation scheme for mmWave communications. As the authors indicate, the $k$-NN approach has good performance for noisy training data while it does not require any knowledge or assumptions about the data distribution. In [34], $k$-NN was used for classification of line-of-sight and non-line-of-sight conditions. In this context, a tenfold cross-validation was performed where the accuracy of the classification was analyzed with the testing and training data. An accuracy of about 96.3 and 94.3% was obtained for pathloss, and an accuracy of 94.5 and 93.3% was obtained for power delay profile at 28 and 39 GHz, respectively. Finally, in [35] the authors proposed a novel MIMO transmission scheme for pattern recognition. Simulation results verified that the proposed $k$-NN approach provided a flexible tradeoff between complexity and achievable bit error rate.

To the best of the authors’ knowledge, this is the first attempt to leverage adaptive beamforming in 5G mmWave m-MIMO orientations with the $k$-NN approximation. The rest of this paper is organized as follows: In Section II, the considered wireless 5G mmWave multicellular orientation is described, while the proposed m-MIMO antenna design is analyzed in Section III. Section IV continues with the description of the proposed adaptive beamforming approach, along with the ML-assisted framework. To this end, a complexity analysis is provided as well. Results for various KPIs are presented in Section V, while concluding remarks and proposals for future work are provided in Section VI.
The following notation is used throughout this work. An italic variable $\alpha$ or $A$ denotes a scalar, whereas boldface lowercase and uppercase variables $\mathbf{a}$ and $\mathbf{A}$ denote vectors and matrices, respectively. Moreover, $||a||_F$ stands for the Frobenius norm of vector $a$. A calligraphic variable $\mathcal{A}$ denotes a set of $|\mathcal{A}|$ elements. $A^T$ and $A^{H}$ denote the transpose and conjugate transpose of matrix $\mathbf{A}$, respectively. Finally, $A(i,j)$ denotes element $(i,j)$ of matrix $\mathbf{A}$ and $[x]$ the integer part of $x$.

II. 5G MM-WAVE MASSIVE MIMO ORIENTATION

We consider the downlink of a 5G m-MIMO multicellular orientation with $B$ BSs. The total available bandwidth is denoted as $W$. MSs enter the network sequentially, based on a predefined spatial distribution. Each MS ($1 \leq k \leq K$) requests $R_k$ Mbps from its serving BS that can be potentially fulfilled by a proper assignment of physical resource blocks (PRBs) and modulation order (MO) per PRB. Therefore, the transmitted signal over a symbol period can be expressed as [36]:

$$x_k(t) = \sum_{s \in \mathcal{I}_k} \sqrt{p_{k,s}} t_{k,s} x_{k,s} e^{j2\pi f_s t}, \quad 0 < t < T_s$$  \hspace{1cm} (1)

where $\mathcal{I}_k$ is the set of PRBs assigned to the $k^{th}$ MS. Assuming $M_t$ transmitting antennas per beamforming configuration (BC) and $T$ potential BCs (i.e., all possible subsets of transmitting antennas are stored in the set $\mathcal{B}_C$) then $t_{k,s}$ is the $M_t \times 1$ transmission vector (diversity combining mode has been assumed), $p_{k,s}$ is the allocated power to the $s^{th}$ PRB of the $k^{th}$ MS and $x_{k,s}$ is the transmission symbol selected from a predefined constellation (i.e., QPSK, 16QAM, 64QAM). Finally, $T_s$ and $f_s$ are the symbol period and the corresponding frequency of the $s^{th}$ PRB, respectively.

The received signal per MS’s PRB is a superposition of all co-channel signals from the same BS in the case of NOMA transmission (intracell co-channel interference, Intra-CCI) as well as from all other BSs (intercell co-channel interference, Inter-CCI):

$$\mathbf{y}_{k,s} = \left( \frac{p_{k,s}}{T_{L,k,sec(k)}} \right) \mathbf{r}_{k,s} \mathbf{h}_{k,sec(k),s} t_{k,s} x_{k,s} + \sum_{k' \neq k, k' \in \mathcal{M}_{S_0}} \left( \frac{p_{k',s}}{T_{L,k',sec(k')}} \right) r_{k,s} H_{k,sec(k'),s} t_{k',s} x_{k',s}$$

$$+ \sum_{k' \neq k, k' \in \mathcal{M}_{S_0}} \left( \frac{p_{k',s}}{T_{L,k',sec(k')}} \right) r_{k,s} H_{k,sec(k'),s} t_{k',s} x_{k',s} + \mathbf{r}_{k,s} \mathbf{n}_{k,s}$$  \hspace{1cm} (2)

where $\mathbf{y}_{k,s}$ is the $M_r \times 1$ received signal. The first term in (2) is the desired MS signal, while the second/third term denote Intra-CCI/Inter-CCI, respectively. Moreover, $H_{k,sec(k),s}$ denotes the $M_r \times M_t$ channel matrix of the $k^{th}$ MS with respect to its serving sector while $T_{L}$ represents the corresponding total losses (shadowing effects have been included as well). Each entry of $H_{k,sec(k),s}$ matrix has been calculated according to the latest 3GPP specifications for channel modelling [31]. Finally, $\mathbf{r}_{k,s}$ is the maximal ratio combining (MRC) multiplying vector and $\mathbf{n}_{k,s}$ the additive white Gaussian noise.

The corresponding Signal to Interference plus Noise Ratio (SINR) per PRB can be expressed as (averaged over a frame duration and assuming that $E(X_{k,s}X_{k',s}^*) = \delta_{k,k'}$, where $E(x)$ is the mean value of $x$ and $\delta$ stands for the Kronecker delta):

$$\text{SINR}_{k,s} = \frac{p_{k,s}}{T_{L,k,sec(k)}} |r_{k,s} H_{k,sec(k),s} t_{k,s}|^2 - \frac{1}{\sum_{k' \neq k, s \in \mathcal{I}_k} \frac{p_{k',s}}{T_{L,k',sec(k')}} |r_{k,s} H_{k,sec(k'),s} t_{k',s}|^2 + r_{k,s}^H r_{k,s} I_o}$$  \hspace{1cm} (3)

where, for sake of simplicity, Intra- and Inter-CCI appear as a unified interference term. Finally, $I_o$ is the thermal noise level. Considering varying SINR threshold values in order to support different service requirements per MS, downlink transmission powers per PRB can be calculated by solving a linear system of equations:

$$\mathbf{p}_s = \mathbf{C}^{-1} \times \mathbf{D}_s$$  \hspace{1cm} (4)

where $\mathbf{p}_s$ is the $N_s \times 1$ downlink transmission vector of the $N_s$ MSs that have been allocated with the $s^{th}$ PRB, and $N_s \times N_s$ matrix $\mathbf{C}_s$ as well as $N_s \times 1$ matrix $\mathbf{D}_s$ are defined as follows:

$$\mathbf{C}_s(k, k') = \begin{cases} \frac{|r_{k,s}^H H_{k,sec(k),s} t_{k,s}|^2}{T_{L,k,sec(k)}} & \text{if } k = k' \\ -\text{SINR}_{k,s} \frac{|r_{k,s}^H H_{k,sec(k),s} t_{k,s}|^2}{T_{L,k,sec(k)}} & \text{if } k \neq k' \end{cases}$$  \hspace{1cm} (5)

In (5), $\text{SINR}_{k,s}$ is the minimum SINR threshold for the support of the considered transmission rate over the $s^{th}$ PRB of the $k^{th}$ MS. In realistic wireless orientations however, this approach cannot be directly applicable, since MSs would have to perform analytic channel measurements on the received signals of all interfering MSs. In this case, and especially when referring to 5G UDNs, ML algorithms can be applicable towards optimum transmission power assignment [37].

The maximum throughput per PRB will be upper limited according to the Shannon formula:

$$r_{k,s} = \frac{W}{N_{PRB}} \log_2 (1 + \text{SINR}_{k,s})$$  \hspace{1cm} (6)

assuming $N_{PRB}$ available PRBs per BS and equal spectral distribution. Thus, the optimization problem may be formulated as follows:

$$\max \left\{ \sum_{k=1}^{K} \sum_{s \in \mathcal{I}_k} \frac{r_{k,s}}{p_{k,s}} \right\} \hspace{1cm} \text{s.t.} \hspace{1cm} \sum_{s \in \mathcal{I}_k} p_{k,s} = W$$
horizontal orientation. It should be noted at this point that multitude of radiating elements (REs) located in vertical and horizontal orientation. It should be noted at this point that the adoption of a 2D antenna array configuration scheme facilitates the deployment of beamforming techniques [38], thus enhancing the spatial coverage in a multicellular environment. The satisfaction of the former design goals sets a fertile ground for the development of ML techniques, since predefined radiation patterns can be formulated by different sub-arrays through the activation of specific horizontal and vertical REs [39].

To this end, the key role for the whole electromagnetic behaviour of the present antenna configuration is strongly dependent on the RE. In particular, the rounded crossed bowtie antennas, used as an exciter of the reflector, have been rotated at ±45° as shown in Fig. 2. It should be mentioned at this point that both crossed dipoles will have a common feeding port and they will be mentioned as a RE through the rest of this paper, unless otherwise stated. In this sense, each RE is placed above a ground plane in a distance of quarter-wavelength (λ/4) far apart from the first one.

In this context, the proposed antenna array configuration is composed of 21 × 21 REs forming rows and columns as shown in the right subplot of Fig. 2. Such type of antenna schemes increase the degrees of freedom in terms of radiation pattern manipulation since the employment of different phase per RE in concert with the appropriate activation of either the whole array or part of it (subarray) can alter the radiation pattern in the desired azimuth and elevation level. Thus, an implicit steering mechanism is formulated, suggesting a low complexity beamforming technique.

The latter technique is clearly depicted in Fig. 3 where different radiation patterns in azimuth level are formed by the activation of different square sub-arrays of the same antenna configuration scheme shown in Fig. 2. By traversing the

\[
\begin{align*}
\max & \left\{ \frac{1}{W} \sum_{k=1}^{K} \sum_{s \in \mathcal{U}_k} r_{k,s} \right\} \\
\min & \left\{ \frac{1}{K} \sum_{k=1}^{K} \sum_{s \in \mathcal{U}_k} r_{k,s}^2 \right\}
\end{align*}
\]

min \(|BC_b|, 1 \leq b \leq B

s.t.: (C1) \(\text{SINR}_{k,s} \geq \text{SINR}_{k,s}, \, 1 \leq k \leq K, \, s \in \mathcal{U}_k
\)
(C2) \(\sum_{k \in \mathcal{M}_b, s \in \mathcal{U}_k} p_{k,s} \leq P_m, \, 1 \leq b \leq B
\)
(C3) \(\sum_{s \in \mathcal{U}_k} p_{k,s} \leq p_m, \, 1 \leq k \leq K
\)
(C4) \(\sum_{k \in \mathcal{M}_b, s} |\mathcal{U}_k| \leq N_{\text{PRB}}, \, 1 \leq b \leq B
\)
(C5) \(|\mathcal{U}_k \cap \mathcal{U}_k| \leq 1, \, BS(k) = BS(k')
\)

According to (7), the primary goal is to maximize both EE (first term) and SE (second term). Moreover, additional metrics under optimization are considered, such as the Jain’s fairness index (third term) as well as the minimization of blocking probability (BP, defined as the ratio of the number of MSs that were rejected to the total number of MSs that tried to access the orientation) and the number of radiating elements that constitute a particular BC. All derived power levels are upper bounded by the corresponding power thresholds \((P_m/p_m)\), respectively. The fourth constraint ensures that hard blocking due to lack of available PRBs will not take place. According to the final constraint, a PRB can be shared by a maximum of two MSs within the same BS, if NOMA transmission is assumed.

The considered wireless orientation is depicted in Fig. 1. As it can be observed, there are three m-MIMO configurations per BS, each one placed 120° apart, in order to provide full spatial coverage. Moreover, two tiers of cells around the central cell have been considered (i.e., 19 BSs) in order to examine the performance of the proposed adaptive beamforming approach in realistic MU orientations. Hence, throughout the rest of this paper, the set \(\mathcal{BC}_b, l\) will indicate the set of transmitting antennas for the \(l^{th}\) configuration of the \(k^{th}\) BS. In the same context, each configuration will be also referred to as sector through out the rest of this paper.

\section*{III. ANTENNA DESIGN}

The suggested antenna array configuration of the current work is shown in Fig. 2. The main prerequisites of the proposed MIMO-antenna design are the low cost fabrication, the formulation of an adaptive dual polarized radiation pattern as well as the development of a reduced hardware complexity array. In order to accomplish the aforementioned requirements, a square 2-D antenna array is employed to host a multitude of radiating elements (REs) located in vertical and horizontal orientation. It should be noted at this point that

![FIGURE 1. Deployed m-MIMO multicellular orientation.](image-url)
FIGURE 2. The geometric characteristics of a reflector with a crossed rounded bowtie as an exciter and its radiation pattern are shown in the left panel while the composition of them in a square array is shown in the right panel.

panels of Fig. 3 from top to bottom, it is conveniently spotted that the directivity of the main lobe is gradually enhanced, as it is expected, since the number of activated elements (forming inner square arrays) increases as well. It should be emphasized that the activation of square sub-arrays can be extended to arbitrary sub-array configurations, as represented in Fig. 4, providing a convenient and efficient way to exploit the electromagnetic behaviour of all the possible sub-array combinations of the proposed antenna array configuration. Hence, up to 51 different BCs can be formed in total, including 10 inner square arrays, 40 rectangular arrays and the activation of 1 central RE. Further simulations proved that the maximum obtained steering angle of the beam is 30°, as beyond that the sidelobes govern the radiation pattern.

Even though the characteristics of a crossed rounded bowtie RE refer to a common crossed dipole antenna, it can easily alter its electromagnetic properties by a simple manipulation of its physical characteristics [40]. In this context, a careful study of the effect of flare angle on return loss of the RE was carried out proving that the appropriate value of flare angle for the suggested antenna array configuration is 60°. In addition, the insertion of stubs among the REs can further achieve not only high isolation (reduced mutual coupling) but also circular polarization [41]. Thus, crossed bowtie antenna arrays are suitable for low-power applications in anti-interference MIMO wireless local area networks. Hence, such type of antenna arrays can mitigate the effects of mutual coupling among the radiating components. Therefore, all the antenna field properties have been computed with the method of moments (MoM), applied in a 3D computational model, taking into consideration the total mutual coupling among the REs on the proposed antenna array configuration [42].

It should be noted here that the proposed antenna array configuration utilizes a hybrid beamforming method in order to reduce the complexity of digital beamforming and at the same time enhance the performance of analogue beamforming. In particular, the digital beamforming architecture is carried out at the stage of baseband signal processing. The latter stage is located at the end of the analogue beamformer which controls the phase of the signal at each RE [43]. Consequently, hybrid beamforming constitutes a critical point of the current study since the proposed ML implementation is strongly dependent on the efficiency and accuracy of the employed phased shifters. Hence, a hybrid beamforming design facilitates the implementation of various ML techniques not only in 5G but also in the forthcoming 6G communication systems.

IV. ADAPTIVE BEAMFORMING IN MASSIVE MIMO SYSTEMS

A. ALGORITHM DESCRIPTION

The proposed adaptive beamforming approach is described in Algorithm 1, considering a particular MC snapshot (the corresponding counter is denoted as mc). In Step 1, the corresponding sets indicating the available PRBs for transmission per BS are initialized (i.e., $S_b$). At the initial state, the central RE per BS’s sector is activated and stored in the set $RE_{b,1}$. For every new potential MS that tries to access the network (denoted as $k$), function define_PRBs returns the minimum number of allocated PRBs for the requested transmission rate and modulation order per PRB. As it will be described in the results section, $MO_k$ can have three distinct values,
namely 2/4/6 for QPSK/16QAM/64QAM modulation type, respectively. Afterwards, the channel gain vector matrix for the \( b^{th} \) BS (\( \mathbf{CG}_{b,c} \)) is generated and sorted as depicted in line 6. The assigned PRBs in the MS are stored in the set \( \mathcal{U}_k \). Transmission vector matrix formulation and power management for all MSs take place in lines 7-10. To this end, \( \mathbf{x}\lambda_{\text{ml}}(\mathbf{A}) \) is the eigenvector corresponding to the maximum eigenvalue of matrix \( \mathbf{A} \).

If no power outage occurs either in BS or MS level, then the new MS is admitted in the network (line 13, where reject flag \( r_f \) is set to zero) and all related sets are updated (line 25). In the opposite case, an additional BC is selected from the available set of configurations. It should be mentioned at this point that in each \( \mathcal{BC}_{b,l} \) set the potential BCs are stored in \( \mathcal{X} \) in ascending order. Therefore, the goal is to select the minimum number of REs for acceptable QoS to all MSs. However, if none of the BCs can fulfill this goal, then the potential MS is rejected from the network (line 19) and all related parameters are restored to their previous values (line 20). The MC simulation comes to an end either if power outage or lack of available PRBs is triggered in at least one of the active BSs. In this case, all output KPIs are calculated: EE, SE, \( \text{BP} \), as well as the maximum number of REs per configuration (denoted as \( \text{max}_T\text{x} \)).

It becomes apparent from the above that the selection of the appropriate BC can be a computationally demanding task, since multiple calculations can take place, according to MSs’ orientation and throughput demand. Therefore, an ML-assisted beamforming approach is alternately used, based on the \( k\text{-NN} \) approach. To this end, the input to the \( k\text{-NN} \) algorithm is an \( \mathbf{X}_{\text{ML}} \) matrix (denoted as \( \mathbf{X}_{\text{ML}} \)), which indicates the requested throughput in the angular space of each sector (line 39, assuming a subcarrier spacing equal to 60 kHz and 12 subcarriers per PRB). Moreover, \( \phi_k \) denotes the angle of the \( k^{th} \) MS with respect to its serving BS. The output, stored in matrix \( \mathbf{Y}_{\text{ML}} \), is a single number where the selected BC has been encoded. In order to avoid overlapping entries, in cases of similar spatial distributions (line 43, where \( \mathbf{O}_{1 \times p} \) indicates a row matrix of \( p \) zero elements) the final selection is based on total downlink transmission power minimization. In this case, the corresponding row is removed from \( \mathbf{X}_{\text{ML}} \) matrix (line 45, where this row is assigned with a null entry).

In our approach, 3000 independent samples were used per simulation scenario. Once the generated set of samples was finalized, it was further decomposed to a training set containing the 70% of the initial entries, as well as to a validation set with the remaining 30% of the initial entries. Afterwards, training was performed with the help of Matlab [42] using a 5-fold cross validation procedure. The \( k\text{-NN} \) approximation provided the best results in terms of accuracy (i.e., 98%) compared to other clustering approaches, such as support vector machines or neural network clustering, since there is a straightforward relationship among the requested throughput in a BS’s angular space and the generated BC. Hence, once the training is finalized, the exhaustive BC search can be omitted, since the algorithm can provide the most appropriate BC for a particular distribution of throughput demand.

B. COMPLEXITY ANALYSIS

In the case of exhaustive BC calculations (it will be referred to as non-ML throughout the rest of this paper) for each new entry in the orientation, the algorithm would have to search over \( N_{\text{BC}} \) BCs for the one that ensures acceptable QoS to all MSs, with minimum number of REs. Hence, the worst case scenario in terms of computational complexity will take place if the capacity in active BSs has reached its upper limit and all potential BCs have been exhausted. Since there are \( N_{\text{PRB}} \) PRBs per BS and each MS is assumed to request \( U_{\text{PRB}} \) PRBs, the capacity is upper limited by \([N_{\text{PRB}}/U_{\text{PRB}}]\). Consequently, complexity will be upper limited by:

\[
\left( \frac{N_{\text{BC}}}{2} \right) \times \left[ \frac{N_{\text{PRB}}}{U_{\text{PRB}}} \right] \times \left[ 1 + \left( \frac{N_{\text{PRB}}}{U_{\text{PRB}}} \right) \right]
\]

which represents all BC calculations for all active MSs.

On the contrary, in the case of ML-assisted beamforming, the goal is to reduce computational complexity and avoid exhaustive beamforming calculations. To this end, transmission power levels and all associated parameters will be updated only when the existing m-MIMO configuration in an active sector is different from the output of the \( k\text{-NN} \) approximation. Therefore, complexity is now proportional to \([N_{\text{PRB}}/U_{\text{PRB}}]\), which is significantly reduced compared to the previous case of non-ML beamforming.

V. PERFORMANCE EVALUATION

Simulation results are presented in Figs. 6–13, where the cumulative distribution function (CDF) curves of SE, EE, \( \text{BP} \) as well as of the maximum number of REs in the topology are depicted. All simulation parameters are summarized in Table 1. Since the goal of the adaptive beamforming framework is the provision of acceptable QoS to MSs in cases of an increased spatial distribution, non-uniform traffic has been assumed, as shown in Fig. 5. In this context, there is one hot spot area per BS, where its location may vary per
Algorithm 1: The Proposed Adaptive Beamforming Approach

1: \( S_b \leftarrow \{1:N_{PRB}\}, (1 \leq b \leq B) \)
2: initialize \( \mathcal{R}E_{b,l}, 1 \leq l \leq 3, ml \leftarrow 0, \ r_u \leftarrow 0 \)
3: \( k \leftarrow k + 1, b \leftarrow BS(k) \)
4: \( U_{PRB} \leftarrow \text{define}_{_{_{PRB}}} (R_k, MO_k) \)
5: \( \mathbf{C}G_{k,S_b} \leftarrow [||\mathbf{H}^H_k,sec(k),S_b||_F/TL_k,sec(k),S_b] \)
6: \( [\mathbf{C}G_{k,S_b}, U_{k}] \leftarrow \text{sort} (\mathbf{C}G_{k,S_b}, U_{PRB}) \)
7: for \( s \in U_k \) do
8: \( t_{k,s} \leftarrow x(\mathbf{r}_m(H^H_k,sec(k),H_k,sec(k),s)) \)
9: update \( p_{k',s}, 1 \leq k' \leq K \)
end for
10: end if
11: Set \( P_{l,b} \leftarrow \sum_{k' \in \mathcal{M}S_{b,s}\in U_k} p_{k',s} \ (1 \leq b \leq B) \)
12: if \( \sum_{s \in U_k} p_{k',s} \leq p_m, 1 \leq k' \leq K \) and \( P_{l,b} < P_m \) then
13: \( rf \leftarrow 0 \)
else
14: while (\( |BC_{k,l}| > 0 \)) and (\( rf > 0 \)) do
15: \( \mathcal{R}E_{b,l} \leftarrow BC_{k,l}(\text{argmin} (|Q'|)) \)
16: \( BC_{b,l} \leftarrow BC_{b,l} - \mathcal{R}E_{b,l} \)
17: update \( \mathbf{H}^H_{k',sec(k'),s}, t_{k',s}, p_{k',s}, P_{l,b} \)
18: for all \( k' \in \mathcal{M}S_{b,k}, \ s \in U_k \) do
19: \( \text{if} \ \sum_{s \in U_k} p_{k',s} \geq p_m \) for the \( k' \text{th} \) MS or \( P_{l,b} > P_m \)
then
20: \( rf \leftarrow 1, \ r_u \leftarrow r_u + 1 \)
21: restore \( \mathbf{H}^H_{k',sec(k'),s}, t_{k',s}, p_{k',s}, BC_{b,l}, P_{l,b} \)
22: end if
end while
end if
24: end if
25: if \( rf \leftarrow 0 \) then
26: \( S_b \leftarrow S_b - U_{k}, \ \mathcal{M}S_{b} \leftarrow \mathcal{M}S_{b} \cup k \)
else
27: if \( P_{l,b} > P_m \) or \( |S_b| < U_{PRB} \) then
28: MC simulation terminates
29: \( EE(mc, 1) \leftarrow \frac{\sum_{k=1}^{K} R_k}{\sum_{k=1}^{K} \sum_{s \in U_k} p_{k',s}} \)
30: \( SE(mc, 1) \leftarrow \sum_{l=1}^{3} \sum_{s \in U_k} p_{k',s} \sum_{l=1}^{3} \sum_{s \in U_k} p_{k',s} \)
31: \( \max_{mc}, 1 \leftarrow \max_{1 \leq b \leq B, 1 \leq j \leq 3} (||\mathcal{R}E_{b,l}||) \)
else
32: \( \text{go to line 3} \)
end if
34: \( k \leftarrow \text{NN sampling and training} \)
35: if \( ml < N_{ML} \) then
36: \( ml \leftarrow ml + 1, \ R_b \leftarrow O_{1 \times 180} \)
37: for all \( k \in \mathcal{M}S_{b} \) do
38: \( \mathbf{R}_b(\phi_k) \leftarrow \mathbf{R}_b(\phi_k) + MO_k 	imes 12 \times 60 \times U_{PRB} \)
end for
39: \( X_{ML}(ml, :) \leftarrow R_b \)
else
40: \( \text{end if} \)
end if

In all the presented results, two beamforming approaches have been considered: In the first case (non-ML), the appropriate BC per case is selected according to the previously described algorithm. In the second case, which will be referred to as ML throughout the rest of the paper, the ML framework of the previous section is employed. Moreover, two traffic scenarios have been assumed: In the first case, all PRBs per MS use QPSK modulation type. In the second traffic scenario, higher order modulation types per PRB can be supported. In particular, the 50% modulation type of the active MSs use QPSK/16QAM/64QAM modulation type per PRB, respectively. Therefore, the requested throughput per MS may vary from 7.2 Mbps (15 PRBs/MS, QPSK modulation type per PRB) up to 64.8 Mbps (15 PRBs per MS, 64QAM modulation type per PRB). Finally, throughout the rest of this paper, all previously mentioned output metrics (KPIs) will be compared with respect to their mean values.

As it can be observed from Fig. 6, the SE for traffic scenario 1 is improved for 5 PRBs per MS (i.e., 21 bps/Hz), since in this case an increased number of MSs can be supported compared to the case of 15 PRBs per MS. Results are aligned with the ones presented in [14] and [15], where
TABLE 1. Simulation parameters.

| Parameter                          | Value/Assumption |
|------------------------------------|------------------|
| Tiers of cells around the central cell | 2                |
| Cell radius (m)                    | 500              |
| Total bandwidth (MHz)              | 100              |
| Subcarrier spacing (kHz)           | 60               |
| Pathloss model                     | UMa              |
| Carrier frequency (GHz)            | 28               |
| MC snapshots per scenario          | 10^4             |
| Antenna elements per MS            | 2                |
| Beamforming configurations (N_Bc)  | 51               |
| Required $E_b/N_0$ (dB) for QPSK/16QAM/64QAM modulation | 9.6/16.4/22.7 [44] |

Traffic scenario-1 QPSK modulation per MS’s PRB

Traffic scenario-2 50% of MSs with QPSK modulation per PRB
30% of the MSs with 16QAM modulation per PRB
20% of the MSs with 64QAM modulation per PRB

SE reaches 22 bps/Hz. This is also the case with the work presented in [45], when maximal ratio combining transmission is assumed. It is interesting to note at this point that in both cases of PRB assignment (i.e., 5 and 15 PRBs per MS) the ML-assisted beamforming framework attains practically the same performance as in the non-ML case, which validates the accuracy of the proposed approach. Moreover, as it becomes apparent from Fig. 10, SE is improved in the second traffic scenario. In particular, it reaches 36 bps/Hz for 5 PRBs per MS. In this case, the number of MSs with higher order modulation per PRB is significantly increased compared to the first traffic scenario.

Fig. 7 manifests that EE in traffic scenario 1 is improved when considering 15 PRBs per MS (i.e., 5 Mbits/J). Results come in agreement with the ones presented in [12], where EE reaches 4.5 Mbits/J. This is also the case with the work presented in [46], where the EE value is upper limited by 5 Mbits/J for SE values ranging from 20 to 30 bps/Hz. In this case, the generated directional beams as presented in Section III, leverage high data rate transmission for MSs, thus leading to an overall improvement of EE. It should be also noted at this point that as in the previous case of SE, the ML-assisted EE values come in agreement with the corresponding non-ML ones. However, this comes at the cost of increased $BP$, as derived from Fig. 8. In particular, for 15 PRBs per MS, $BP$ reaches 1.4%/3.5% for the non-ML/ML cases, respectively. This increment, which is almost 2%, is directly related to the $k$-NN performance accuracy loss, as mentioned in the previous section.

Fig. 11 shows clearly that EE is reduced in traffic scenario 2 (i.e., 2.7 Mbits/J for 5 PRBs per MS). In this case, although
highly directional beams can be formulated in order to ensure QoS for a group of high data rate MSs, unavoidably, another group of MSs will be located near the 3dB beamwidth of the specific beams. Hence, transmission power will be increased. It is worth noticing though that SE improvement between the two traffic scenarios for 5 PBRs per MS reaches 70% (i.e., 36 bps/Hz in traffic scenario 2 and 21 bps/Hz in traffic scenario 1), which is significantly improved compared to the corresponding EE loss (i.e., 30%, when comparing 2.7 Mbits/J in traffic scenario 2 and 3.9 Mbits/J in traffic scenario 1). For 15 PRBs per MS, then SE improvement reaches again almost 40% (i.e., 27 bps/Hz in traffic scenario 2 and 16 bps/Hz in traffic scenario 1). In the same context, EE loss is limited to 23% (4.1 Mbits/J in traffic scenario 2 and 5 Mbits/J in traffic scenario 1, as previously mentioned).

As in the case of the first traffic scenario, BP is likewise increased when considering the ML beamforming framework in the second traffic scenario (i.e., 2.5%/6.5% for the non-ML/ML cases, respectively, and 15 PRBs per MS). It should be emphasized at this point however that the high values of BP for all the examined orientations stem from the fact that no service downgrade has been considered, in order to establish a fair comparison between the two traffic scenarios. Hence, MS satisfaction in terms of acceptable QoS turns into a binary process: if the requested downlink transmission rate cannot be fulfilled either due to power outage or due to lack of available PRBs in the serving BS, the MS will be automatically rejected from the network. This is more evident in the ML-beamforming framework, oriented to further reduce algorithmic complexity. Therefore, if an MS cannot be served by the output configuration of
the k-NN model, no additional BCs will be examined, thus increasing BP.

It becomes apparent from Figs. 6 and 10 that SE curves have increased standard deviation (std) values for 15 PRBs per MS. In particular, std is 2.5/3.2 bps/Hz for traffic scenario 1 and 4.6/5.4 bps/Hz for traffic scenario 2, when considering 5/15 PRBs per MS, respectively. In this case, due to the increased amount of required transmission power for 15 PRBs per MS, BP is likewise increased, as previously mentioned. Consequently, the number of accepted MSs in the network and thus SE are subject to more intense variations compared to the case where 5 PRBs per MS are allocated. In EE calculations (Figs. 7 and 11), then the gain in the second traffic scenario among 5/15 PRBs per MS is increased, as it is evident from the relative positions of the corresponding group of curves. In this case, although EE values are reduced compared to traffic scenario 1 as previously explained, an increasing number of PRBs per MS consequently results in an increased number of MSs within the 3dB beamwidth of a highly directional generated beam with higher order modulation types per PRB.

Finally, in Fig. 9 the CDF curves of the maximum number of REs per sector for various modulation types (traffic scenario 2).

![Empirical CDF curves of the maximum number of REs per sector for various modulation types (traffic scenario 2).](image_url)

the non-ML approach. In this context, as previously mentioned, multiple beamforming calculations are omitted, since the selected BC is directly related to the output of the k-NN approximation.

**VI. CONCLUSION**

The performance of an adaptive beamforming approach has been evaluated, when deployed in 5G mmWave massive MIMO multicellular orientations. The presented approach has been also leveraged by the deployment of a supervised ML algorithm. On one hand, beamforming is performed according to a predefined set of configurations that can provide improved spatial coverage for a wide variety of traffic distributions, and on the other hand ML assisted beamforming can significantly reduce overall execution times. Extensive system level simulation results were carried out that cover various cases of requested throughput demand per active user. Performance evaluation proved that in the ML framework there is a fundamental tradeoff among complexity reduction (in terms of algorithmic calculations and hardware equipment) and blocking probability, since in this case exhaustive beamforming calculations that could potentially allow the admittance of more users in the orientation are omitted.

Ongoing work includes among others the extension of the ML framework with deep reinforcement learning in order to cover a wide variety of 5G topologies as well as the dynamic placement of relay nodes that can further improve spatial coverage.

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