

RESOURCE ALLOCATION AND IMPACT ANALYSIS OF THE SYSTEM PARAMETERS ON PERFORMANCE IN MULTI-CELL MASSIVE MIMO NETWORKS

Samira Mujkić^{1,2}, Suad Kasapović¹

Abstract: This paper investigates the energy-efficient resource allocation algorithm for a massive multiple input multiple output (MIMO) system, in which each base station adapts the number of antennas to the daily load profile. Our paper examines the effect of two user location distribution (ULD) models, on the energy-efficiency (EE) of load adaptive masive MIMO system. We propose a resource allocation strategy to adapt the number of antennas based on tracking variations of ULD and cell loading maximizing the EE. We also evaluate impact of cell size, available bandwidth and output power level of the BS on EE at different cell loading.

Keywords: energy efficiency, massive MIMO, traffic load, user location distribution

INTRODUCTION

The new technology of the 5th generation (5G) standard that will most significantly increase energy efficiency is a technology called massive MIMO. Massive MIMO will also increase network bandwidth and thus meet the current demand for higher data rates.

With excessive power consumption in wireless communications networks, beside spectral efficiency (SE), EE has become another significant metric for evaluating the performances of wireless communications systems. The energy consumption of a base station (BS) with no load is at least half of the maximum energy it consumes at the peak. Therefore, it is very important that 5G networks are able to adapt their power consumption with temporal changes of load [1]. In order to improve the energy efficiency of the 5G base station it is necessary to develop joint optimization schemes and algorithms to save computational and transmission power in the main unit of the base station and radio frequency (RF) chains together. Management of radio resources requires the establishment of strategies and algorithms that will use limited resources in the most efficient way. Due to the constant changes in the cells, it is necessary to establish a dynamic allocation of resources where the radio resources will follow the changes and be adaptable to them. Resource allocation established in this way should result in high energy efficiency.

In [2] the authors developed a joint beamforming and user scheduling algorithm based on fractional programming and the Hungarian algorithm. The Hungarian algorithm

selects the optimal set of users from the much larger pool of potential users, for a given set of beamforming weights, in polynomial time. Furthermore, several works [3] the authors analyse how the three main design parameters; namely the number K of active user equipment (UEs), the M number of antennas at the base station (BS), and the transmit power must be chosen to improve EE.

A low-complexity resource allocation scheme has been recently investigated in the literature. In particular, authors in [4] developed an algorithm that jointly optimizes the number of antennas, user selection and power allocation in a multi-user massive MIMO system, while the work in [5] optimizes user scheduling, power allocation and beamforming in MIMO networks implementing user-centric clustering.

In [6] the authors investigated the impact of power amplifiers (PA) dimensioning on the energy efficiency of load adaptive massive MIMO system. A common algorithm for antenna selection and resource block (RB) allocation was created in [7] together with power optimization algorithm. Resource allocation method presented in [8] optimally select data and pilot powers along with the training duration and maximize the spectral efficiency for the three deferent receivers. The paper [9] also analysed the energy efficiency of a system with a large number of antennas where the transmission antennas were selected and the authors proposed two algorithms for the selection of transmitting antennas based on the application of sequential and binary search algorithms.

In [10] the authors show that during low traffic demand, e.g., late night, it is optimal to turn off a fraction of the

¹ Faculty of Electrical Engineering, University of Tuzla, Bosnia and Herzegovina

² Correspondence email: samira.mujkic@untz.ba

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antennas while minimizing total power consumption if the power consumption in the transceiver circuits is taken into account along with the RF amplifiers.

This paper investigates the energy-efficient resource allocation algorithm for a massive MIMO system, in which each base station has a large number of antennas and it adapts the number of antennas to the daily load profile. Two user location distribution (ULD) models, central focused (CF) ULD and boundary focused (BF) ULD, are defined in this paper. The formed ULD model defines two coverage areas with different user densities. ULD analysed in this paper is similar to models in [11] but in our paper we have also analysed the influence of certain system parameters on EE for different ULD model at different cell load. In particular, we aim at bringing new insights on how the number M of antennas at the BS, the number K of active UEs, and other system parameters should be chosen in order to achieve maximal EE. It was assumed that cells are identical in terms of all configuration and aspects.

Each BS is modelled as an M/G/m/m state dependent queue [12] in order to more easily calculate the probability of a certain state of the user in the network. This dependence is a consequence of that the user rate directly depends on the number of users served by the base station simultaneously.

To the best of our knowledge, there is no existing work that provides mechanism to cope with the daily load variation and maintain high EE throughout the day in a massive MIMO network. This paper aims to fill this gap in the literature where we consider efficiency taking into account daily load variation, the number of base station antennas and user load distribution. We make the following contributions:

- We derive a new downlink EE equation by considering beside M , K , also the effect of daily load variations for the massive MIMO system.
- We derive adaptive antenna system that adapts the number of active BS antennas to daily load variations.

The remaining of this work is organized as follows: in Section 1 we present the created model for system, power consumption, distribution of user location and traffic. The second section describes EE maximization problem. Simulation results for the created system sub-scenarios are described in Section 3. At the end of the paper there is a conclusion.

1. ANALYSED MODELS

1.1. System model

This paper presents a massive MIMO system that considers only the downlink of a multi-cell system. The cells are hexagonal and each has its own BS.

The number of users served by each BS is denoted by K_i , while the number of used antennas is denoted by M_i . In network with massive MIMO the ratio of these two units must be $M_i > K_i$. Users have devices with one antenna. User devices with multiple antennas are not considered due to the computational complexity.

The architecture of analysed massive MIMO system is shown in Figure 1.

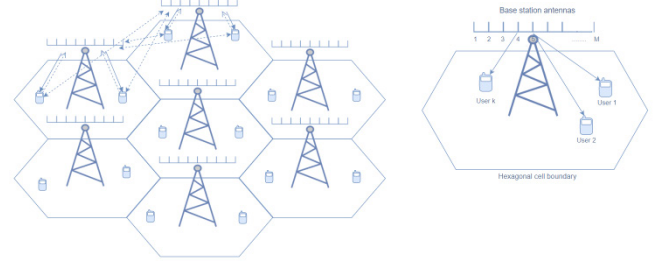


Figure 1: The architecture of massive MIMO system

BS transmits a constant output power P_c , which is distributed equally among PAs and each PA is connected to one antenna element. The Rayleigh channel, which remains static within a time-frequency coherence block of $U=B_c T_c$ symbols, is considered, where B_c is coherence bandwidth, while T_c represent coherence time.

The large-scale fading is assumed to be the same for all the antennas, because the distance between any UE and the BS is much larger than the distance among the antennas.

We assume that all BSs and UEs employ a time-division duplex (TDD) protocol and zero-forcing (ZF) precoding and that BSs have perfect channel state information (CSI).

One of the basic definitions of massive MIMO energy efficiency (in bits/Joule) represents EE as a ratio of spectral-efficiency (sum-rate in Mbit/s) and total consumed power (in Joule/s) [13]:

$$EE(K_i, M_i) = \frac{\sum_{k=1}^{K_{\max}} R(k, M_i)}{p_i^{\text{total}}(K_i, M_i)} \quad (1)$$

The user rate at UE_z in the cell i is expressed as:

$$R_{UE_z}(K_i) = \left(1 - \frac{\alpha K_{\max}}{T_c B_c}\right) \log_2 \left(1 + \frac{Q_1 Q_2}{Q_3 + Q_4}\right) \quad (2)$$

Where necessary overhead for channel acquisition is equal to

$$\left(1 - \frac{\alpha K_{\max}}{T_c B_c}\right)$$

α is the pilot reuse factor, $K_{\max}$ is the maximum number of served users and $T_c B_c$ is time-frequency coherence block during which channel remain static. $Q_2 = p(M_i/K_i)$ represents mean transmit power per user and $Q_2 = (M_i - K_i)$ is the effective array gain. Average noise power that interferes with the signals coming from the serving base station is:

$$Q_3 = \frac{B\delta^2}{d_i(UE_z)}$$

whereas

$$Q_4 = \sum_{j=1}^J \left\{ \frac{d_j(UE_z)}{d_i(UE_z)} pM_j \right\}$$

is average inter-cell interference power. The path loss from the serving BS at origin cell i to UE_z is equal to $d_i(UE_z)$ while $d_j(UE_z)$ is path loss from interfering BS.

1.2. Power consumption model

The power consumption (PC) is the sum of the PA when the average output power is p and power consumed by different analogue components and digital signal processing. When the transmitter is equipped with a large number of antennas circuit power consumption dominates the system power consumption. We propose a new refined circuit power consumption model for massive MIMO systems:

$$P_i^{total}(K_i, M_i) = P_{PA}(p) + P_C = M_i P_{PA}(p) + P_{C0}(K_i) + P_{C1}(K_i, M_i) + P_{FIX} \quad (3)$$

where $P_{PA}(p)$ is the total input power of a traditional power amplifier (TPA) and can be approximated as [14], [15]:

$$P_{PA}(p) \approx \frac{1}{\eta} \sqrt{p \cdot P_{max,PA}} \quad (4)$$

where η is the maximum TPA efficiency and $P_{max,PA}$ is maximum output power.

Prominent research directions to minimize power amplifier losses include [16]:

- dimensioning the power amplifier,
- use of low peak-to-average-power-ratio (PAPR) techniques and
- PA-aware design.

$P_{C0}(K_i)$ is a part of circuit power and is dependent on the number of simultaneously served users K_i while $P_{C1}(K_i, M_i)$ depends also of the number of base station antennas M_i .

For circuit power consumption we use the model proposed in [17]:

$$P_C = P_{FIX} + P_{CE} + P_{TC} + P_{CD} + P_{LP} \quad (5)$$

where P_{FIX} is fixed power with constant quantity for control signalling, site cooling, load independent power of baseband processing and backhaul infrastructure. P_{CE} is power of the channel estimation process. P_{TC} accounts for the power consumption of the transceiver chains and is given by $P_{TC} = MP_{TC} + P_{syn} + KP_{UE}$ where P_{BS} is the power per RF chain at the BS required to run the circuit components, P_{syn} is power consumed by the local oscillator (LO) and P_{UE} is power required by all circuit components of each single-antenna UE. P_{LP} is power consumed for linear processing operations at the base station and P_{CD} is power of the channel coding P_{COD} and decoding P_{DEC} .

Total baseband power when the BS serves K_i users simultaneously with M_i antennas can be expressed as:

$$P_{BB}(K_i, M_i) = P_{C0}(K_i) + P_{C1}(K_i, M_i) = \sum_{k=1}^{K_{max}} R_i(k) (P_{COD} + P_{DEC}) + P_{syn} + \frac{BK_i^3}{3T_C L_{BS}} + P_{BS} + \frac{BM_i K_i}{L_{BS}} \left(2 + \frac{1}{T_C} \right) + \frac{3BM_i^2 K_i^2}{L_{BS}} \quad (6)$$

where $\sum_{k=1}^{K_{max}} R_i(k)$ is the total distance-dependent rate calculated for one base station according to (2), whereas L_{BS} is BS_i computational efficiency and B is the bandwidth.

1.3. User Location Distribution model

Two coverage areas, central and boundary, are defined in this paper. They are divided with radius r_D , but such that it holds $r_D > r_{min}$ and $r_D < r_{max}$. r_{min} represents the radius of the circle within which are not distributed users due to the requirement that the minimum distance of the user from BS is 35 m ($r_{min} = 35$ m) and r_{max} represents the radius of the circumscribed circle of hexagon. Figure 2 shows geometry of coverage areas.

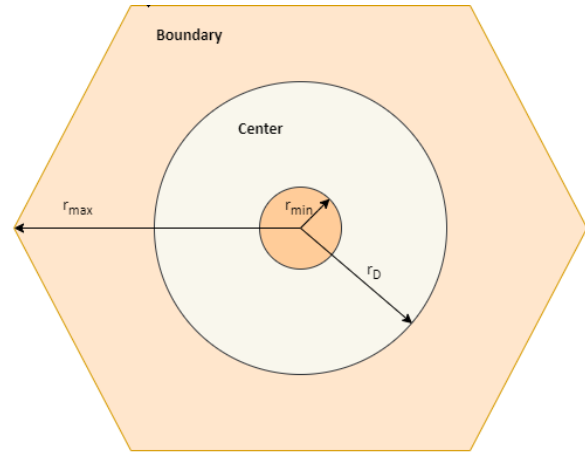


Figure 2: Geometry of coverage areas

Central area users are distributed within a circle defined by radius r_D except area defined by radius r_{min} . Due to the above in the area of the central area we have the difference between the radii r_D and r_{min} . Border area users are distributed in the band outside the circle with radius r_D and inside the hexagon with the radius of the circumscribed circle r_{max} . A set of weighting factors $\gamma = \{\gamma_c, \gamma_b\}$ is assigned to each area and it is a function of time, so that it can take different values during the day. The sum of weighting factors at any time instant is always unity i.e., $\sum \gamma = 1$. As the cell is split up into two coverage areas, we have a set of radii $r = \{r_D, r_{max}\}$ and in our main simulation scenario we have that $r = \{300, 500\}$ than a set of weighting factors for BF ULD are $\gamma_{BF} = \{0.3, 0.7\}$ and a set of weighting factors for CF ULD are $\gamma_{CF} = \{0.8, 0.2\}$.

1.4. Traffic model

We consider the daily load profile proposed for data traffic in Europe [18] and model the load at each BS as a state-dependent M/G/m/m queue [11] where M is distribution of the inter-arrival time of users, G the distribution of the service time, m the number of servers, and m is the capacity of BS. State dependency results from the fact that the user rate depends on the number of users served by the BS simultaneously. The M/G/m/m queue dictates that for exponential user arrival with rate λ and general distribution of service rate. Number of servers is equal to a maximum number of users.

The change in the number of users at BS will result in the change of the service rate for every user. Service rate for n users that are served simultaneously will be $\mu(n)$, but if there is new user served by BS the service rate will change to $\mu(n+1)$. Also, when BS stops with serving one user there is a change in service rate and it becomes $\mu(n-1)$.

The steady state probabilities for the random number of users n in the BS i are modelled as:

$$\pi_i(n) = \left[\frac{[\lambda E[T_1]]^n}{n! \mu(n) \mu(n-1) \dots \mu(2) \mu(1)} \right] \pi_i(0) \quad (7)$$

$$\pi_i(0)^{-1} = \sum_{j=0}^{m=K_{\max}} \left\{ \left[\frac{[\lambda E[T_1]]}{\mu(n) \mu(n-1) \dots \mu(2) \mu(1)} \right]^j \frac{1}{j!} \right\}$$

where $\pi_i(0)$ is the probability when no user in cell i , $E[T_1]$ is the expected service time when there is only one user in BS, $\mu(n) = (R_i(n))/(R_i(1))$ is the service rate and it is ratio of the data rate of n users in BS, to data rate of one user. For different user states the data rates are calculated according to (2).

In a queuing system with no buffer space, the blocking probability is probability of having $K_{\max}$ number of users. As in the works [6], [19], [1] and [11], the probability of simultaneously serving $K_{\max}$ number of users is 0.02.

Average number of users in other time intervals is calculated using $\lambda_{\max}$ which is determined by $\pi_i(K_{\max}) = 0.02$. Corresponding average number of users at time instant t in which cell load is x_t is determined by $\lambda_t = \lambda_{\max} * (x_t / 100)$.

2. PROBLEM FORMULATION

The problem to be solved is the maximization of the EE of the massive MIMO system described in Section 1. In order to simplify the problem solving, the assumption that the multi-cell environment is symmetric in terms of all configuration and aspects was used. Based on these assumptions, the number of antennas for all cells will be the same. In order to achieve better EE in the massive MIMO system, this paper propose system model that has

the ability to adapt the number of active antennas for any user states, taking into account the interference from the surrounding BSs. In this system BS discovers the most energy efficient number of active antennas M_{opt} for a given number of users by maximizing EE:

$$M_{opt} = \arg \max : \frac{\sum_{k=1}^{K_{\max}} R(k, M_i)}{p_i^{total}(K_i, M_i)} \quad (8)$$

$$\text{constraint: } M_i \geq \frac{P_c}{P_{\max, PA}} * 10^{PAPR} \quad M_i \geq k + 1$$

The first constraint is due to keep PAPR of the transmitted signal at 8 decibel (dB) and second constraint is requirement of ZF precoding.

In addition to the optimal value of the number of antennas for a given number of users, it is very important to determine a weighted-average value of M_{opt} during time instant t is:

$$M_{avg}^t = \left[\sum_{k=1}^{K_{\max}} \pi_i(k) * M_{opt}(k) \right] \quad (9)$$

In order to analyse the performance of our proposed adaptive system model, we also created a system model that has a fixed number of antennas active all the time without regard to changes in network. This model is called a fixed or reference system model.

First action of the proposed algorithm is to determine the global optimal number of antennas and users (M_{glopt}, K_{glopt}). This global optimum of antennas is used to initialize the number of antennas at all BS in fixed system and also the initial value of the number of antennas in adaptive system. We do not have the closed form expression for the $M_{opt}(k)$, but since M and k are integer values, the optimum number of antennas can be found by exhaustive search over each user state. According to (8) the vector of antennas that maximizes EE was found and then according to (9) the weighted average optimal number of antennas, M_{avg} was calculated. Number of antennas at a certain number of users and load $M_{iterate}$ is iteratively updated with M_{avg} , until it converges.

Similar algorithm was proposed in [11] where authors have analysed the same conditions but ULD model is different.

Proposed strategy, which contains previously described steps is shown in Algorithm 1. Due to the assumed configuration symmetry in all cells, our proposed strategy was performed only for one considered cell. Optimization algorithm with the same approach has been already proposed in [20].

Algorithm 1: Optimization strategy

Constraint for M: $M_{min} \geq \left\lceil \frac{P_c}{P_{max,PA}} * 10^{0.8} \right\rceil$ & $M_{min} \geq k + 1$

Initialization:

$$\begin{aligned} M_{max} &\leftarrow M \\ K_{max} &\leftarrow M/2 \end{aligned}$$

For $m \in [M_{min}, M_{max}]$ **do** $k \in [1, K_{max}]$ **do**
 $EE_{glopt}(M_{glopt}, K_{glopt}) \leftarrow \max: \frac{\sum_{k=1}^{K_{max}} R(k, M_i)}{P_{total}(K_i, M_i)}$

End for

While Converged=false

For all user state $k \in [1, K_{max}]$ **do**
 $M_{opt}(k) \leftarrow \operatorname{argmax}_{M_{iterate}} \frac{\sum_{k=1}^{K_{max}} R(k, M_{iterate})}{P_{total}(K_i, M_{iterate})}$

$$\begin{aligned} R_{opt}(k) &\leftarrow \operatorname{argmax}_{M_{iterate}} R(k, M_{iterate}) \\ \pi_i(k) &\leftarrow \left[\frac{[\lambda E[T_1]]^k}{n! \mu(k) \mu(k-1) \dots \mu(2) \mu(1)} \right] \pi_i(0) \end{aligned}$$

end for

$$M_{avg} \leftarrow \left[\sum_{k=1}^{K_{max}} \pi_i(k) * M_{opt}(k) \right]$$

end while

3. RESULTS AND DISCUSSION

The Matlab software was used to test the performance of the massive MIMO system, which in simulation environment consists of 19 regular hexagonal cells. Monte-Carlo insertion method was used to place 10 000 test points in each cell. Test points are not distributed in the circle with cell radius of 35 m, which is determined by the minimum distance from the base station.

In order to avoid border effects and achieve a situation where all base stations receive interference from all directions equally, a wrap-around topology was used. More precisely, for each combination of user device and base station, eight alternative base station locations are considered and it is determined which one has the shortest distance to the user device.

A bandwidth of 20 MHz was used for communication with a total receiver noise power of -96 dBm. The coherent bandwidth is 180 kHz, and the coherent time is 10 ms, which results in a coherent block of 1800 samples.

The channel model uses a Rayleigh fading channel, and the path attenuation factor is 3.76, which determines the loss of transmission of the base station signal to the user device. The base station operates on a carrier frequency of 2 GHz.

In order to find optimal size of the cell, bandwidth and base station output power level additional sub-scenarios have been created in which influence of certain system parameter on EE was analysed.

3.1. Influence of cell size on performance of massive MIMO system

In this section we analyse how different cell size influence the performance of the considered system model in the central and boundary coverage areas. Influence of cell size on EE and average user rate (UR) was analysed for cell sizes of 500 m, 1000 m and 2000 m.

In comparison to BF ULD, better results of EE and average UR are achieved for CF ULD in each considered cell size, but both ULD models, achieved better results for adaptive system.

Higher energy efficiency is achieved for scenarios with a smaller cell size. However, when the cell is too small, the antenna gain and spectral efficiency will be reduced, which is why it is important to determine the size of the cell.

The results for the average UR for BF ULD and all considered cell sizes are shown in Figure 3, and for CF ULD in Figure 4.

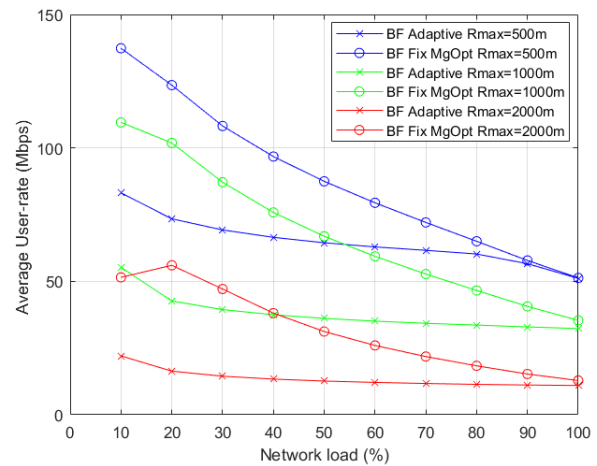


Figure 3: Average UR for BF ULD at different cell size.

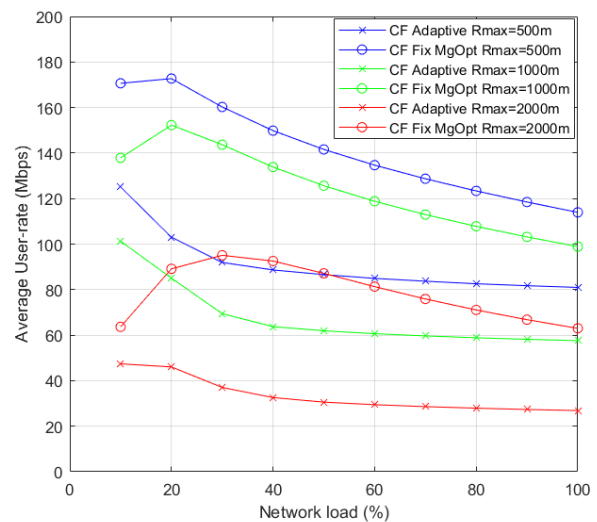


Figure 4: Average UR for CF ULD at different cell size.

The best results of the average UR are achieved for a fixed system, CF ULD and a cell size of 500 meters. With the increase of the network load, the average UR in the adaptive system decreases and for network loads of 10-30% there is a significant decrease in average UR, while for network loads of 30-100% the average UR has almost the same values

The fixed antenna system has approximate values for all network load values, which is expected because this model of antenna system always has the same number of activated antennas, regardless of the network load and the number of users. In order to compare the adaptive and fixed system results, EE gain was used, which represents a simple ratio of these two quantities, i.e. $(EE_{adaptive} - EE_{fixed}) / EE_{fixed}$. EE gain of adaptive antenna system has excellent results for both, the CF and BF ULD, and increases with the increase of the cell size, but it decreases with increasing cell load. The corresponding EE gain for cell radius of 500 m, and cell load of {10, 50, 100} % for BF is {204.96, 39.56, 0}% and for CF is {244.32, 125.88, 49.51}%. The achieved values of EE gain for different cell radii are shown in Figure 5.

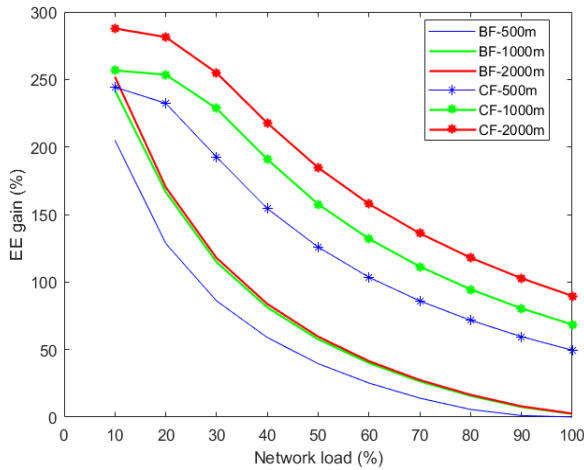


Figure 5: EE gain for different cell size and ULD model

The conclusion for this part of the analyses in which the influence of cell size was considered is the following:

- The maximum number of active users K_{max} , and EE increases with decreasing cell size,
- M_{max} and the difference in EE gain between the fixed and adaptive antenna system decreases with decrease cell size.
- As cell size and network load increase, average UR in the adaptive antenna system decrease.
- Based on the results of all sub-scenarios, the best network performance was achieved when $R_{max}=500$, which represents the optimal cell size.

3.2. Influence of bandwidth on performance of massive MIMO system

Allocation of additional spectrum in 5G, which will bring wider bandwidths is necessary. The maximum channel bandwidth defined for Frequency range 1 (< 6 GHz) is 100 MHz, while the minimum channel bandwidth defined for Frequency range 2 (24–54 GHz) is 50 MHz and the maximum is 400 MHz.

This section analyses the influence of the bandwidth values on the EE and average UR. The values for which the impact is analysed are values from 20 MHz to 100 MHz with a step of 20 MHz.

Figure 6 shows the results for EE of network load for BF ULD at different bandwidth values (20 MHz, 60 MHz and 100 MHz), while Figure 7 shows the results for CF ULD. EE and average UR are increased when bandwidth is increased, for both CF and BF ULD, but CF ULD achieved better results for all analysed bandwidth values. The difference between the achieved results of CF and BF ULD is not significant, but when bandwidth and network load are increased, this difference is also increased in benefit of CF ULD.

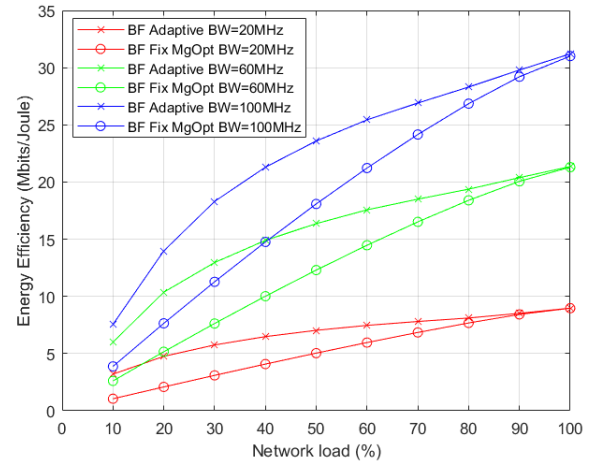


Figure 6: EE for BF ULD at different bandwidth values.

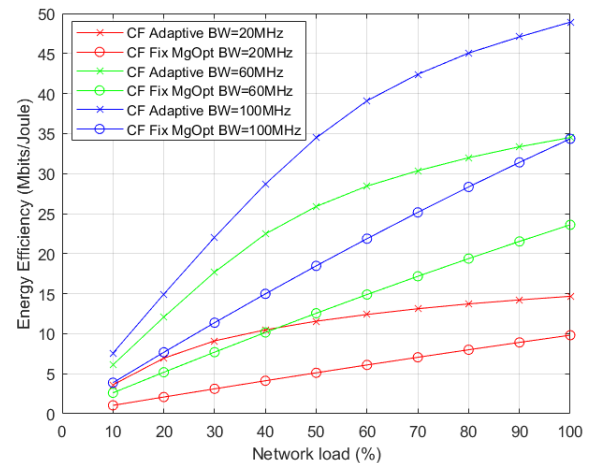


Figure 7: EE for CF ULD at different bandwidth values.

In analysed scenarios with different bandwidth, the proposed adaptive system achieved better results than the fixed one. The results of the adaptive system are significantly better, when the bandwidth is increased. The difference between the achieved results of EE for fixed and adaptive system in BF ULD is smaller and with increasing network load EE achieves approximate values in both considered models. When the bandwidth is increased from 20 MHz to 60 MHz, the EE value is doubled for BF ULD and network loads of 20-100%. Also, with CF ULD the same level of EE improvement was achieved in the mentioned two scenarios with different bandwidth but for network loads of 30-100%.

Further increase in bandwidth, i.e. up to 100 MHz still results in a significant increase in EE but in a smaller ratio. In the case of CF ULD and a bandwidth of 100 MHz, an EE of slightly less than 50 [Mbit/Joule] was achieved, which is three times higher than in the case of the bandwidth of 20 MHz used in the baseline scenario. Also, BF ULDs achieve a threefold increase in EE when the bandwidth is 100 MHz compared to the scenario with a bandwidth of 20 MHz. Fixed antenna system, in both ULD models at the aforementioned network load range values, also achieved three times the EE for the 100 MHz bandwidth compared to the sub-scenario having a 20 MHz bandwidth.

Figure 8 and Figure 9 show the results of the achieved average UR for BF and CF ULD, respectively. The obtained results show that in this scenario, higher average UR were achieved in the fixed system model and in the case of CF ULD. For both ULD models, the highest average UR was achieved with a bandwidth of 100 MHz, which is more than 4 times higher than the baseline scenario with 20 MHz, i.e. the increase in bandwidth increases and the average speed per user.

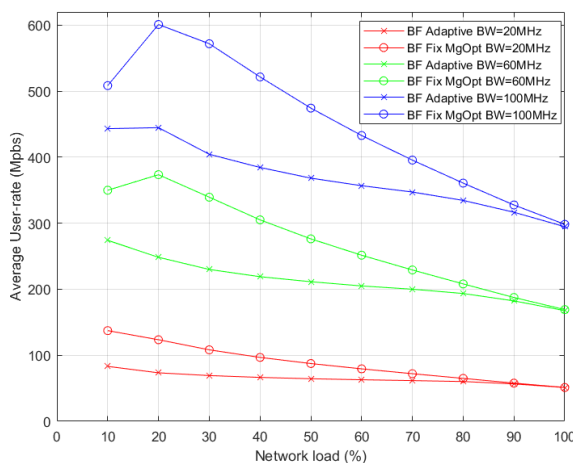


Figure 8: Average UR for BF ULD at different bandwidth values.

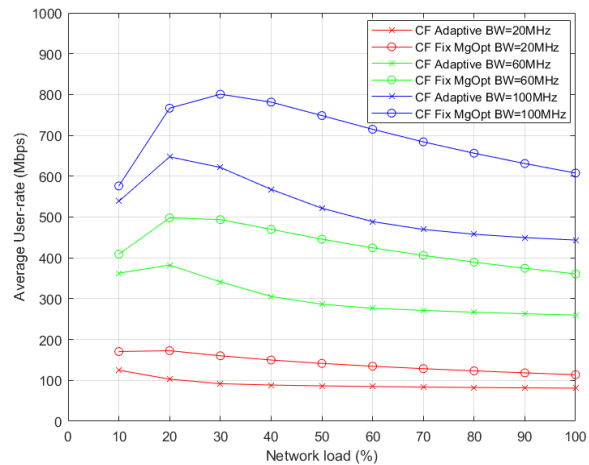


Figure 9: Average UR for CF ULD at different bandwidth values.

With BF ULD, the difference between the average UR of the fixed and adaptive system model decreases with increasing network load, so that at a network load of 90%, these two models have almost the same values. On the other hand, with CF ULD, for almost all network load values, there is an equal difference between the average speed per user of a fixed and adaptive system model. For CF ULD there is the biggest difference between the results of the fixed and adaptive system model. This difference is smaller at lower network loads in scenarios with higher bandwidth.

Due to the abovementioned, the highest EE gains were achieved in the case of CF ULD, which are significantly higher for network loads up to 40% in the baseline scenario (BW = 20 MHz), after which approximate values were achieved. The results for EE gain and loss of UR are shown in Figure 10 and Figure 11. Despite these improvements, maximum number of users and antennas are significantly reduced with increasing bandwidth so that a scenario with the bandwidth

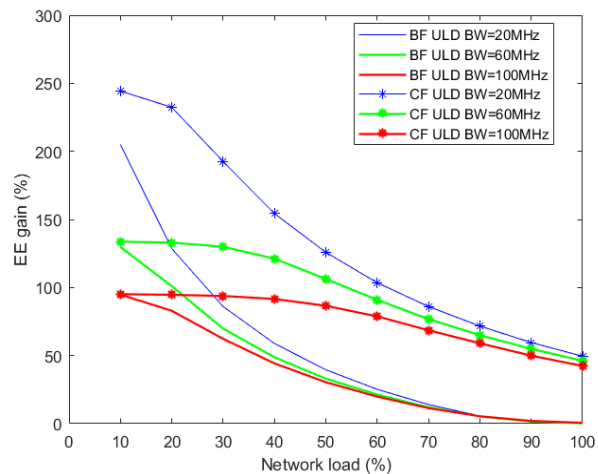


Figure 10: EE gain at different network load, bandwidth and ULD model

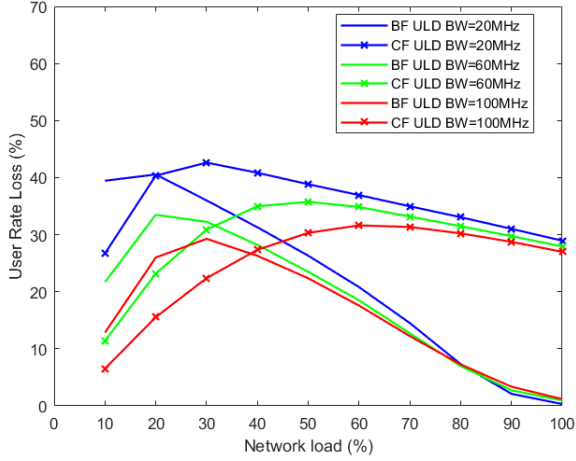


Figure 11: User-rate loss at different network load, bandwidth and ULD model

of 100 Hz have $M_{max}=96$ and $K_{max}=43$. Therefore, choosing the appropriate bandwidth will depend on the compromise reached between the number of users served simultaneously and the desired level of performance for those users.

3.3. Influence of the output power level of the BS on performance of massive MIMO system

For the analysis of the influence of the output power level of the BS on the performance of the system under consideration, 4 scenarios were created. The values for which the impact is analysed are values from 10 W to 40 W with a step of 10 W. The output power level of the BS is directly related to the number of active antennas, as well as the EE, which is why it is very important to analyse how the increase in network load affects the activation of the antenna at the base station. BF ULD requires significantly higher activation of antennas with increasing network load than CF ULD. In both cases of ULD, the highest activation of antennas was for $P_c=40$ W. CF ULD achieved the best results when $P_c=20$ W and in this case it is necessary to activate an average of 60 antennas at maximum network load. The best results for BF ULD are achieved, when $P_c=10$ W and in this scenario it is necessary to activate on average 3 times more antennas at maximum network load i.e., 185 antennas.

Figure 12 shows the results of the optimal number of active BS antennas in the case of CF ULD and both system models (adaptive and fixed).

The results have the same trend of behaviour, i.e. the largest M_{opt} is for $P_c=40$ W, and the smallest for $P_c=10$ W for both system models. Increasing the number of users in the network linearly increases the number of optimal antennas, but in the case of higher network load (100%) a higher M_{opt} is recorded, compared to the network load of 20%. The representation of EE for all analysed scenarios with different P_c values is shown in Figure 13.

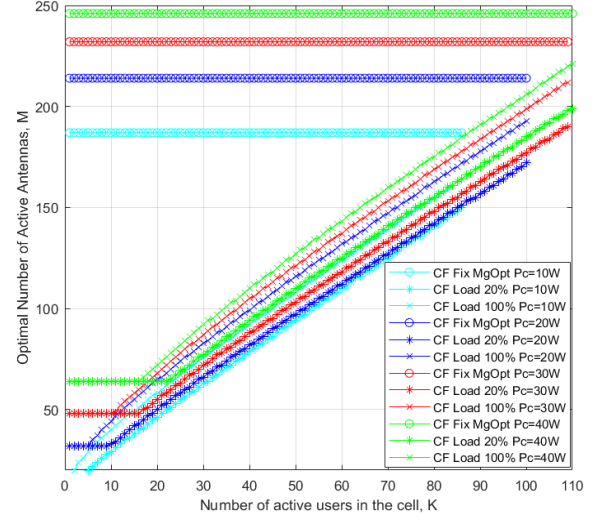


Figure 12: Optimal number of active antennas

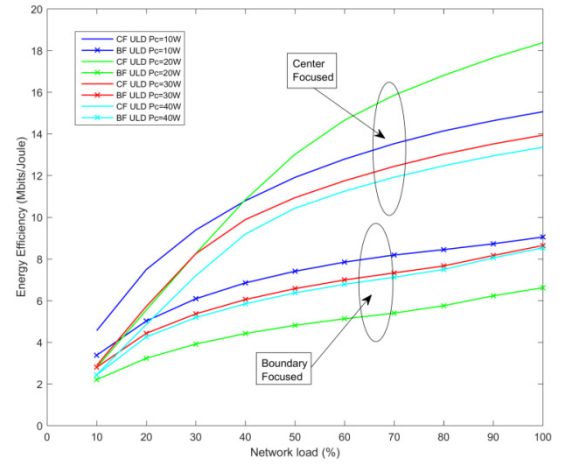


Figure 13: EE at different values of output power level of the BS and ULD models.

4. CONCLUSION

Massive MIMO technology is considered crucial for the further development of wireless networks, and due to its characteristics and capabilities, it is the basic technology for achieving the requirements set for the 5G standard and the future 6G standard. In this paper, we investigate resource allocation of a load adaptive massive MIMO system with different ULD models. Our developed resource allocation scheme is different from the existing ones due to the fact that it jointly optimizes the user load distribution, number of BS antennas and cell loading.

We also determined the impact of cell size, available bandwidth and output power lever of the BS at different cell loading on EE and average UR. When the number of service antennas in massive MIMO systems is determined, other system parameters can be adjusted (radiation power, number of users, etc.) to achieve higher spectral

efficiency at the cost of reduced energy efficiency, and vice versa.

The results of the analysis confirm that EE increases with decreasing cell size, however, decreasing cell size also affects the reduction of antenna array gain. Spectral efficiency is reduced when the cell size is too small. Also, as cell size decreases, transmission power decreases as users will be closer to the base station. In the scenario with a bandwidth of 100 MHz, the achieved EE is three times higher than in the baseline scenario (20 MHz).

Also, the results of the proposed adaptive system model are compared with the results of the fixed system under the same conditions in the network, all with the aim of determining the improvement of the system's performance when the number of BS antennas is adjusted to the network condition. The results showed that the adaptive system model achieved better results for EE and average UR in all scenarios. For all-network loads and for both system models, adaptive and fixed system, worse results for EE and average UR were obtained for the BF ULD case, which is a consequence of interference from neighbouring base stations.

The paper assumes that the CSIs for the receiver are perfectly known. However, this assumption may be unrealistic. An interesting and important problem is to analyse the behaviour of the proposed system model when the CSI data are unreliable. Also, it is very important to deal with the pilot contamination. Future research should investigate the appropriate design of frequency reuse factors during training and power control to reduce pilot contamination effect.

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BIOGRAPHY

Samira Mujkić received the B.S., M.S. and Ph.D. degrees in electrical engineering from the University of Tuzla, Tuzla, Bosnia and Herzegovina, in 2011, 2014 and 2022, respectively. From 2012 to 2014, she was a Teaching Assistant and from 2014 to 2017 she was a Lecturer with the College of Computer Science and Business Communications eMPIRICA, Brcko, Bosnia and Herzegovina. She currently works at the Government of the Brcko District of Bosnia and Herzegovina. Her main research interests include radio resource allocation, wireless communications, MIMO and massive MIMO systems.

Suad Kasapović received the B.S. degree in Electrical Engineering from the University of Tuzla, Tuzla, Bosnia and Herzegovina, in 1996. He then received the M.Sc. and Ph.D. degrees in fields Telecommunications and Informatics at the Faculty of electrical engineering and computing, from the University of Zagreb, Croatia in 2002 and 2007, respectively. He is currently an Associate Professor with the Department of Telecommunications, University of Tuzla. His general research interests include signal processing and wireless communications, with emphasis on MIMO communication systems, practical issues in 5G systems, and wireless sensor network, and etc.