DYNAMIC RESOURCE ALLOCATION AND ACTIVITY MANAGEMENT FOR IMPROVING ENERGY EFFICIENCY AND FAIRNESS IN 5G HETEROGENEOUS NETWORKS

A THESIS SUBMITTED TO

THE GRADUATE SCHOOL OF ENGINEERING AND SCIENCE

OF BILKENT UNIVERSITY

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR

THE DEGREE OF

MASTER OF SCIENCE

IN

ELECTRICAL AND ELECTRONICS ENGINEERING

By

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August 2016

Dynamic Resource Allocation and Activity Management for Improving Energy Efficiency and Fairness in 5G Heterogeneous Networks
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We certify that we have read this thesis and that in our opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science.

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ABSTRACT

DYNAMIC RESOURCE ALLOCATION AND ACTIVITY MANAGEMENT FOR IMPROVING ENERGY EFFICIENCY AND FAIRNESS IN 5G HETEROGENEOUS NETWORKS

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August 2016

The higher energy consumption of Heterogeneous Networks (HetNet) compared to Macro Only Networks (MONET) raises a great concern about the energy efficiency of HetNets. In this thesis a dynamic activation strategy is proposed which changes the state of small cells between Active and Idle according to the dynamically changing user traffic in order to increase the energy efficiency of HetNets. Moreover, both inter-tier and inter-cell resource allocations are adjusted dynamically. The proposed strategy, Dynamic Bandwidth Allocation Dynamic Activation (DBADA), is applied in a small cell deployment where HotSpot regions are located at the cell edge and a small cell is located at the center of each HotSpot. The objective is to maximize the sum utility of the network with minimum energy consumption. To ensure proportional fairness in the network, the logarithmic utility function is employed. To evaluate the performance of the DBADA strategy over the proposed network topology, the median and 10-percent rates and the energy consumed per unit of these metrics are studied. Our simulation results reveal that the DBADA strategy can achieve the highest median and 10-percent rates among other scenarios. In addition, compared to always active scenario for small cells, DBADA decreases the energy consumption per unit of median and 10-percent rates by at least 26% and 21%, respectively.

Keywords: Heterogeneous Networks, Small cell, Dynamic activity management, Dynamic resource allocation, Proportional fairness, Energy efficiency.

ÖZET

5G ÇOKTÜREL AĞLARDA ENERJI VERIMLILIĞI VE ADALETI İYILEŞTIRMEK IÇIN DINAMIK KAYNAK ATAMA VE FAALIYET YÖNETIMI

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Ağustos 2016

Sadece Makro ağlara (MONET) göre enerji tüketimi daha yüksek olan Heterojen ağların (HetNet) enerji verimliliği endişe uyandırmaktadır. Bu tezde HetNet'lerin enerji verimliliğini arttırmak için dinamik olarak değişen kullanıcı trafiğine göre küçük hücrelerin durumunu Aktif ya da Boşta olarak değiştiren bir dinamik aktivasyon stratejisi önerilmektedir. Önerilen çözümde hem katmanlar arası, hem de hücreler arası kaynak tahsisleri dinamik olarak ayarlanmaktadır. Önerilen Dinamik Bant genişliği Tahsisi Dinamik Etkinleştirme (DBADA) stratejisi, merkezine bir küçük hücre yerleştirilmiş HotSpot bölgelerinin hücre kenarlarına yerleştirildiği bir küçük hücreli ağ sisteminde uygulanmaktadır. Amaç, minimum enerji tüketimi ile ağın toplam yararını maksimize etmektir. Ağda orantılı adaleti sağlamak için logaritmik fayda fonksiyonu kullanılır. Önerilen ağ stratejisi üzerinde DBADA stratejisinin performansını değerlendirmek için ortanca ve yüzde 10 veri hızları ve bu ölçütlerin birimi başına tüketilen enerji incelenmiştir. Tezdeki simülasyon sonuçları DBADA stratejisinin literatürdeki diğer çözümlere göre en yüksek ortanca ve yüzde 10 veri hızlarına ulaştığını ortaya koymaktadır. Ek olarak, küçük hücreler için daima aktif senaryosuna göre DBADA stratejisi ortanca very hızı birimi başına enerji tüketimini %26'nın üzerinde ve yüzde 10 veri hızı birimi başına enerji tüketimini ise %21'in üzerinde düşürmektedir.

Anahtar sözcükler: Heterojen Ağlar, Küçük hücre, Dinamik etkinlik yönetimi, Dinamik kaynak ayırımı, Oransal adalet, Enerji verimliliği.

Acknowledgement

I acknowledge all people who contribute to this thesis, specially my supervisor Prof. Ezhan Karaşan. I would like to thank Azita Nouri for her kind support.

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Chapter 1

Introduction

The growth in the number of mobile users and the increase in their required data rates motivate researchers to think about more advanced wireless network topologies [1, 2]. Furthermore, these new topologies should be able to cope with the conventional network planning, where a single Base Station (BS) is responsible for coordinating all the communications that take place within a large cell. Among possible architectures, a heterogeneous deployment of small BSs (SBSs) which is underlaid by a conventional single-BS network is proved to be a promising way for improving both the network coverage and the users quality of experience, which is called Heterogeneous Network architecture [3, 4].

As it is depicted in Figure 1.1, a Heterogeneous Network (HetNet) consists of different tiers with different transmit powers. In HetNets, while macro cell guarantees coverage through the entire network, small cells either provide service for coverage wholes or deliver specific services to a local environment. Depending on their cost and complexity, small cells could be deployed by operator or local providers. Although they enhance conventional networks by expanding coverage and providing special services for local customers, they introduce additional challenges to the service providers.

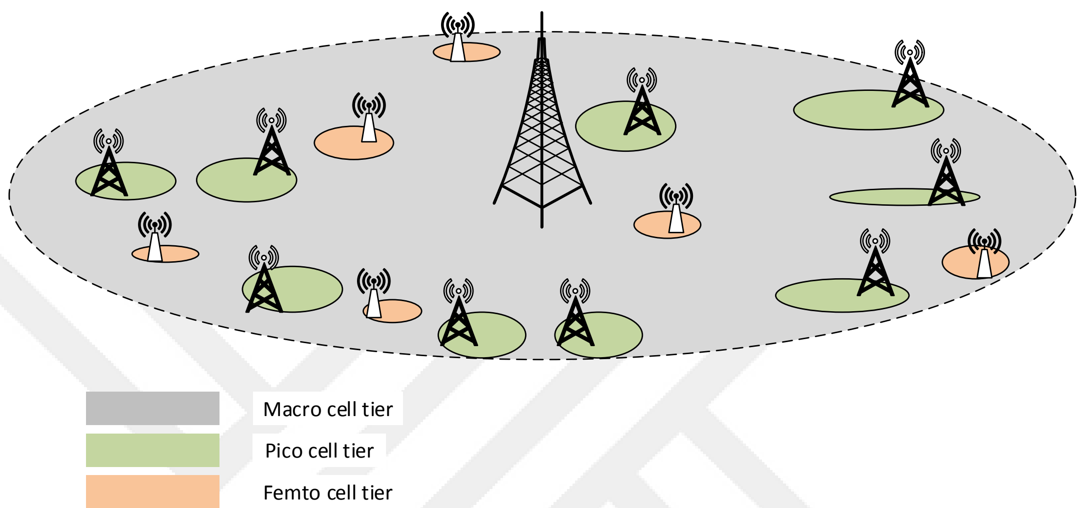


Figure 1.1: HetNet architecture

The direct result of deploying a large number of BSs inside a conventional single-BS cell is an inevitable growth in the network energy consumption. Therefore, right after the emergence of HetNet topology, there has been a great concern about their energy efficient deployment [5–7]. However, according to [8], there are great fluctuations in the number of users in a cellular network. Those fluctuations, which are experienced over time and space, enable us to think about more efficient deployment of small cells. For instance, pushing small cells to Idle state in off-peak hours could be considered to improve the energy efficiency of HetNets [9]. In this strategy, a small cell would be pushed to Idle state if its serving traffic drops below a certain threshold and would switch back to Active state if its traffic passes a threshold. In fact, those two thresholds might not be the same to prevent unnecessary switches. In the case of switching a small cell to Idle state, its associated users would be served either by Macro BS (MBS) or by other SBSs [10].

In addition, as the network evolves toward heterogeneity, an inevitable growth in interferences from other BSs would deteriorate users quality of experience [11]. Thus, the challenges of interference management and resource allocation become more crucial in HetNets [12]. The most important factor which affects the type of resource allocation suitable for a specific deployment is the spatial distribution of small cells within the macro cell area. In dense deployments, where small cells are close to each other reusing resources across multiple small cells would introduce strong intra-tier interference to the system. However, in sparse deployments co-channel deployments result in higher spectral efficiency. Furthermore, according to spatial distance between macro and lower tier, inter-tier resource allocation would be considered. For instance, when small cells are deployed at the macro cell edge and the cell size is large enough, reusing resources across tiers would also increase the spectral efficiency in the system. Nevertheless, in order to obtain higher gains from co-channel deployment, power control [13] and beamforming [14] are proposed in the literature.

Furthermore, according to the high transmit power of Macro BS (MBS), offloading a user to SBS may not be possible even if the user is close enough to SBS. This happens since a user inside a HetNet typically tries to connect to the BS which provides highest instantaneous Signal to Noise Ratio (SNR) which, in plain HetNet, is MBS for most of the users. Therefore, in order to have a balanced load over all cells, authors suggest to add a bias factor to SBS transmit power [15,16]. In this strategy, known as cell range expansion [15], a specific user is associated to the BS which provides highest SNR weighted by its bias factor. Although associating users according to this strategy would result lower instantaneous SNR for some users, it would provide long-term benefits by balancing load across different cells [15].

The problem of energy efficient deployment of HetNets has been investigated in the literature. Authors in [17] propose a dynamic ON/OFF strategy for both uniform and non-uniform user distributions. In this work, the achievable degree of energy efficiency under a certain outage probability is studied. However, the effect of energy saving on the potential improvements of HetNets over Macro

Only Networks (MONETs) has not been studied. In [18], the traffic delay and energy efficiency trade-off in HetNets is investigated. The traffic delay would be a problem in congested cells when the other cells are pushed to Idle state. Nevertheless, by considering a single small cell inside the macro cell they effectively ignore the possible reassociation of users to the other lightly loaded small cells in the same tier, which could reduce the delay penalty in ON/OFF switching strategy. A dynamic ON/OFF strategy over a dynamically changing traffic in an HetNet is studied in [19], where the authors try to maximize energy efficiency of the network. Although their sum rate analysis sheds light on the possible energy efficiency improvement of HetNets, they do not consider fairness among users. Another small cell ON/OFF strategy is introduced in [20], where authors propose a new user association technique together with a dynamic state switching strategy. Their proposed strategy takes into account multiple factors, like small cell resource availability. However, there is no discussion about the energy model for the BSs, which, according to our studies, affects the ON/OFF strategy significantly. A joint partial spectrum sharing and ON/OFF strategy for a two tier HetNet is introduced in [21]. In this work, the coverage probabilities with different reuse factors are examined. However, the lack of enough comparisons, specially with complete orthogonal resource sharing, is observed in their work. Furthermore, they examine the proposed scheme for only uniform distribution of users, which is not the case in most of the scenarios arising in practical situations.

In this work, we study the problem of energy efficient deployment of HetNets. The most important contribution of this work is studying the possible improvement of DBADA strategy in terms of invested energy per bit of information. To this end, we first define an optimization platform, where the objective is to maximize sum utility of the network with minimum energy. Then, by employing a logarithmic utility function, we provide proportional fairness of data rates achieved by users in our system. In addition, by introducing a new parameter to our model we also take the price of energy into consideration. To the best of our knowledge, the potential improvement of dynamic activation strategies in terms of the energy per bit of information has not been studied in the literature. We study the improvement of DBADA strategy in terms of network sum rate, median rate and 10-percent rate. In this study, 10-percent rate refers to the data rate which is guaranteed to be achieved by 90% of users in the system. In addition, the price of a bit of information at the whole network, median user and 10-percent user, in terms of energy, is studied. Our results reveal that by employing DBADA with Proportional Fair Scheduling (PFS), the highest average 10-percent rate and median rate could be achieved. Compared to Picos always Active (Picos Active) strategy with PFS, DBADA with PFS increases the median rate and 10-percent rate by at least 11% and 30%, respectively. Also, a 24% and 11% improvement on median rate and 10-percent rate is observed compared to Macro only scenario. Furthermore, in terms of energy per median rate and energy per 10-percent rate, DBADA with PFS improves the performance by at least 21% and 26%, respectively, compared to Picos Active scenarios. Compared to Macro only scenario, while achieving the same energy per 10-percent rate, DBADA with PFS decreases the energy per median rate by 12%. It is also shown that DBADA with PFS achieves up to 12% and 16% improvements in terms of energy per sum rate compared to Macro only and Picos Active scenarios, respectively.

The rest of this thesis is organized as follows. In Chapter 2, HetNet architecture along with its benefits and challenges are discussed. The problem of utility optimum and energy efficient deployment of a HetNet is introduced and discussed in Chapter 3. In Chapter 4, the numerical results are presented and the thesis is concluded in Chapter 5.

Chapter 2

Heterogeneous Networks (HetNets)

In this chapter, the potential solutions for exploding data demand are provided. The benefits and challenges about the HetNet architecture are also discussed.

2.1 Exploding Data Demand and Possible Solutions

According to [22], the overall mobile data traffic will experience about 8-fold increase from 2015 to 2020, as depicted in Figure 2.1. This explosion in data traffic demand is the result of increasing the number of subscribers, from one side, and the emerging data hungry applications such as Ultra High Definition (UHD) online videos, online gaming, peer-to-peer networking, etc., from the other side. Consequently, operators have been pushed to think about possible solutions to overcome the aforementioned growth in data traffic demand, in the following dimensions,

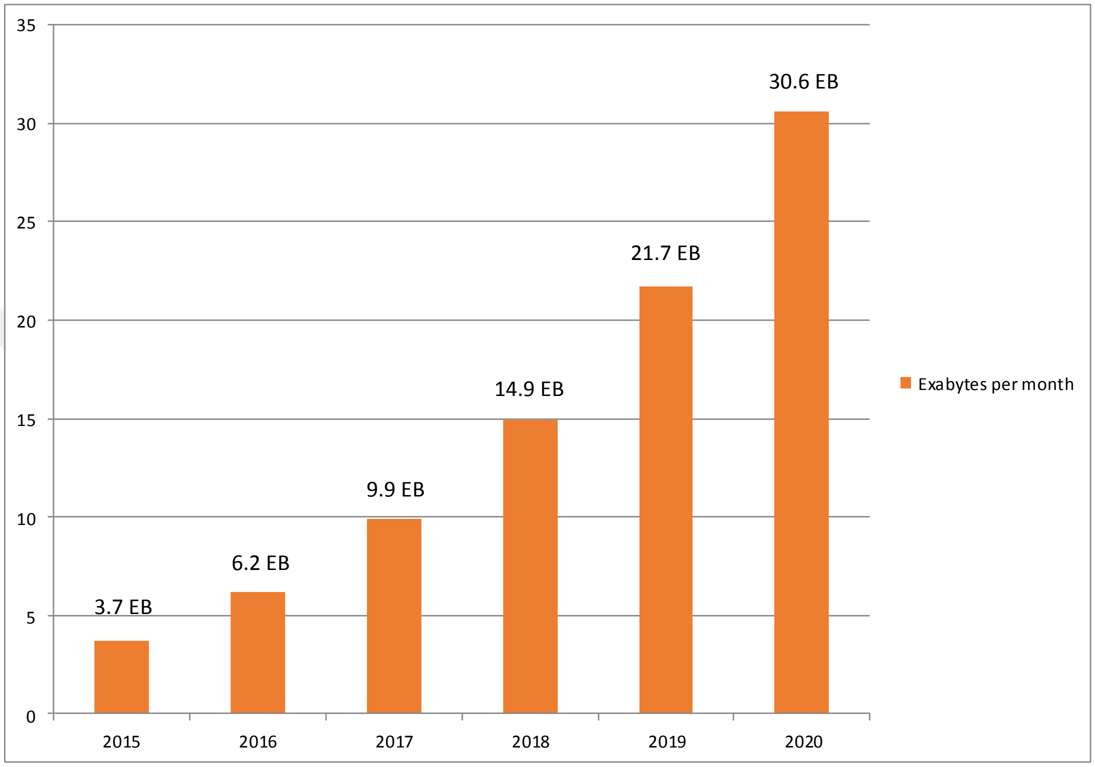


Figure 2.1: Mobile data demand

- *Spectrum extension*, which includes utilizing the unlicensed spectrum, visible light and millimeter wave communications.

- *Increasing spectrum efficiency*, which is enabled by advanced interference coordination, beamforming and massive MIMO.

- *Increasing network density*, which is achievable by Wi-Fi integration and small cell deployments.

Among all the solutions, in this study we are going to explore the possible benefits and challenges of small cell deployments.

2.2 Benefits of HetNets

The most important benefits of small cell deployments can be listed as,

- *Offloading from macro cell*
  By deploying small cells in a macro cell, a part of the excess load of macro cell can be offloaded to small cells, which in turn leaves more space for both small cell and macro cell users. This can not only reduce the centralized computational burden at MeNB, but also brings the possibility of reusing available resources throughout the network [23, 24].

- *Improving coverage*
  Due to their easy deployment, small cells are a good candidate for providing coverage in coverage holes. Furthermore, by deploying small cells at the cell edge of macro cells a significant improvement on cell edge experience could be achieved.

- *Enhancing link quality*
  Bringing APs close to users results in a better link quality, which is an immediate result of shorter communication distance.

2.3 Small Cells and Possible Deployment Scenarios

Small cells, from deployment location point of view, could be categorized as follows.

- *Uniformly Distributed Small Cell (UDC)*
  In UDC configuration, small cells are distributed uniformly throughout the macro cell. The main drawback of UDC is the strong interference, both in uplink and downlink, specially for small cell users. More specifically, since

the macro cell users are supposed to be distributed all over the environment it would not be possible to employ a simple power control scheme, neither in uplink nor in downlink.

- *Cell-On-Edge (COE)*
  In COE configuration small cells are placed on the cell edge of macro cell. COE deployment mainly focuses on the cell edge users' throughput, which is supposed to be improved in LTE Advanced standard [25].

The two configurations are depicted in Figure 2.2 and Figure 2.3.

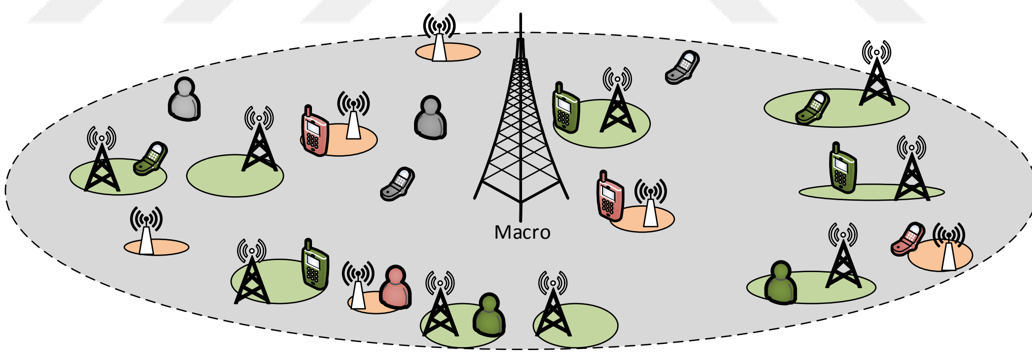


Figure 2.2: Small cell deployment: UDC configuration

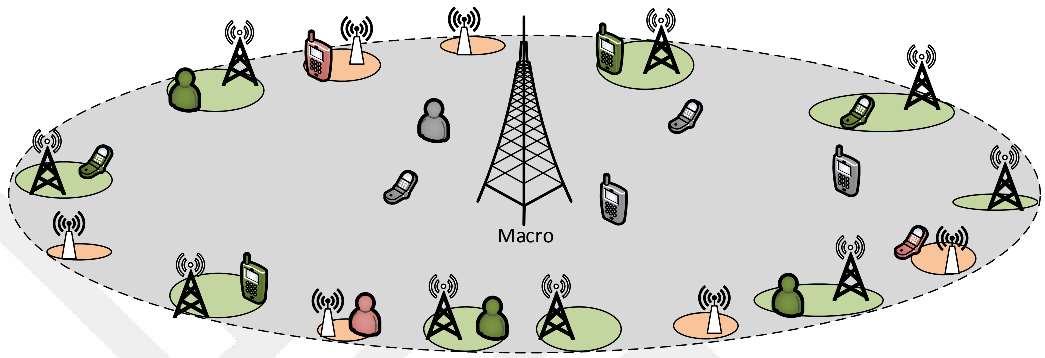


Figure 2.3: Small cell deployment: COE configuration

2.4 Challenges of HetNets

2.4.1 Deployment Aspects

There are various types of SBSs that can be deployed in an HetNet: operator deployed Micro/Pico cells, enterprise Femto cells and user deployed Home eNBs (HeNBs) [3]. The key factor which affects the deployment of a specific small cell is whether it is a closed access or an open access small cell. In closed access scenario, users would be allowed to connect to the small cell if they have permission to do so. In other words, before connecting to a closed access small cell, users should pass an authentication process in order to show their authenticity to the small cell. Deploying small cells in closed access scenario results in easier cell association and interference management. However, closed access is only applicable for the environments where the users are fixed, like people living in a home, or the environments which experience small variations in the users, such as a university department [26]. For the rest of environments, where the users variation is not small enough, open access is the preferred scenario [27].

In the open access scenario, that is usually deployed by the operator [28], users are allowed to connect to the small cell without any authentication, which brings more challenges to operators. The most important challenge of open access scenario is to handle the number of users attempting to connect to a specific small cell. The number of users would become a challenge for operator when it exceeds the maximum load of a small cell. In this case, in order to provide an acceptable level of service to all the users, operator should try to balance the load between different small cells in the environment.

Furthermore, in operator deployed small cells, SBSs should be connected to the backhaul in order for the operator to be able to have control over the small cells [29], such as interference control and load balancing. This functionality is enabled by the X2 interface, as it is introduced in LTE standard [30, 31].

Nevertheless, due to the nature of closed access scenario, which is mostly coordinated by local operators, no X2 interface is required to connect them to backhaul. The deployment aspects of different SBSs are summarized in the following table.

	Access Scenario	Backhaul Connection	Notes
Micro and Pico cells	open access	through X2 interface	operator deployed
Femto cells	closed access	no backhaul connection	consumer deployed

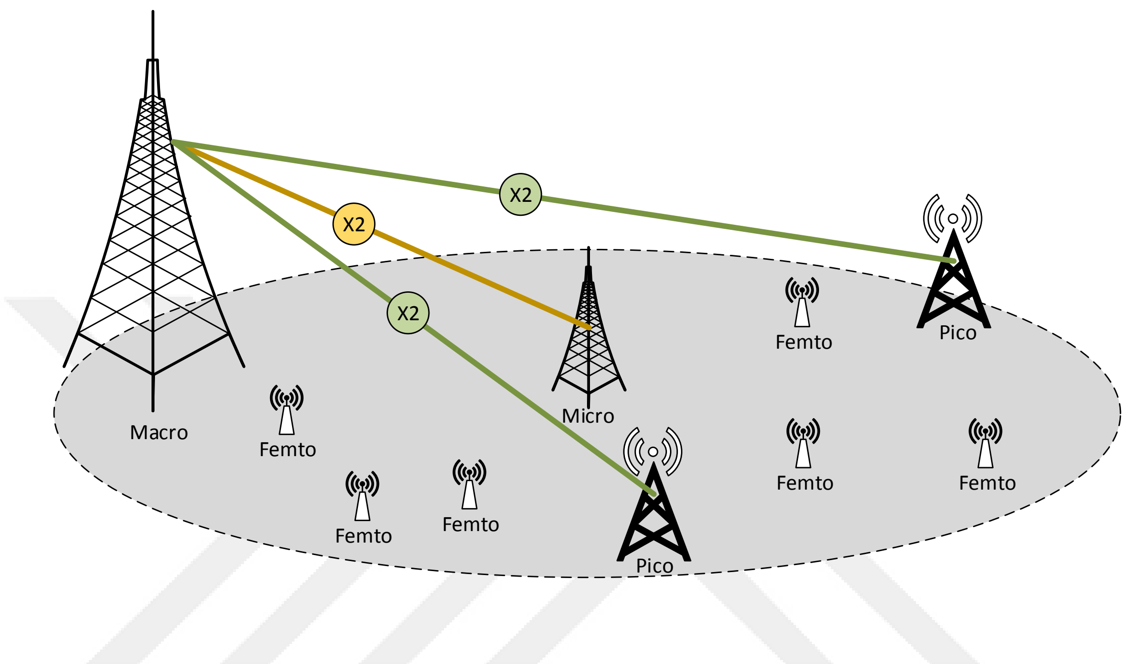


Figure 2.4: Small cell deployment: X2 interface

2.4.2 Cell Association, Load Balancing and Bias

As new small cells begin to operate inside a macro cell, the primary question is how to associate users to cells in a heterogeneous environment. The cell association is usually done based on performance metrics. For instance, the most commonly performance metric is SNR [32], where a user connects to the AP who provides the highest SNR. Another important metric is load balancing, where a user would be associated to a specific AP if its connection satisfies a certain load balancing objective. However, the two performance metrics would not be in the same line for a specific connection in the network. For instance, due to the greater transmit power of MBS most of the users would be connected to it if the performance metric is SNR. However, it would result in a highly congested macro cell while leaving small cells with a few number of users. In order to overcome this problem, biasing strategy is proposed in the literature [33] and the references therein. In this strategy, a user would be associated to small cell even if the small cell provides lower SNR than macro cell, so far as the difference of the two SNR remains below a certain threshold. This strategy provides more balanced load between the macro tier and the lower tiers.

By multiplying the SBS transmit power by a bias factor, we would essentially introduce a trade-off between the network throughput and the load balancing. Therefore, although the biasing strategy seems to be a promising technique for offloading more users from macro cell and providing more balanced load in the network, it may degrade other performance metrics, such as network throughput, fairness, outage, etc. [34]. The degradation would happen due to the congested small cells or the lack of inter-cell interference coordination [34]. In such cases, however, offloading users to small cells would improve the capacity of macro cell users.

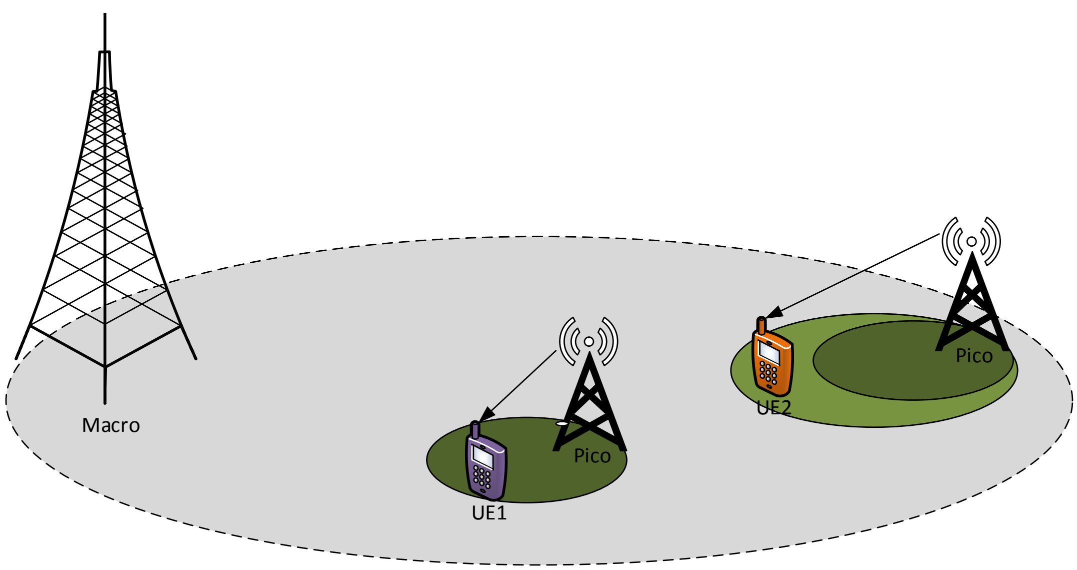


Figure 2.5: Small cell deployment: cell range expansion and biasing

2.4.3 Interference Management

By deploying different class of low power nodes inside a macro cell, the concept of interference management becomes more crucial [35]. This is mainly because the transmission/receiption is no more centralized in HetNets. Specifically, in downlink, users would receive signals from more than a single access point. Not only this, but also due to the closer user-AP distances in small cell deployments, the interferences would be stronger than conventional networks. As it is depicted in Figure 2.6, the interference level at UE1 would also be non-negligible because the MBS transmit power is much stronger than the Pico BS (PBS). Accordingly, although the UE1 is closer to PBS it would also receive a heavy interference from MBS. On the other hand, UE2 experiences undesirable signal too, since its location is close to PBS which would results a significant interference. Thus, downlink interference coordination is an important challenge in small cell deployments.

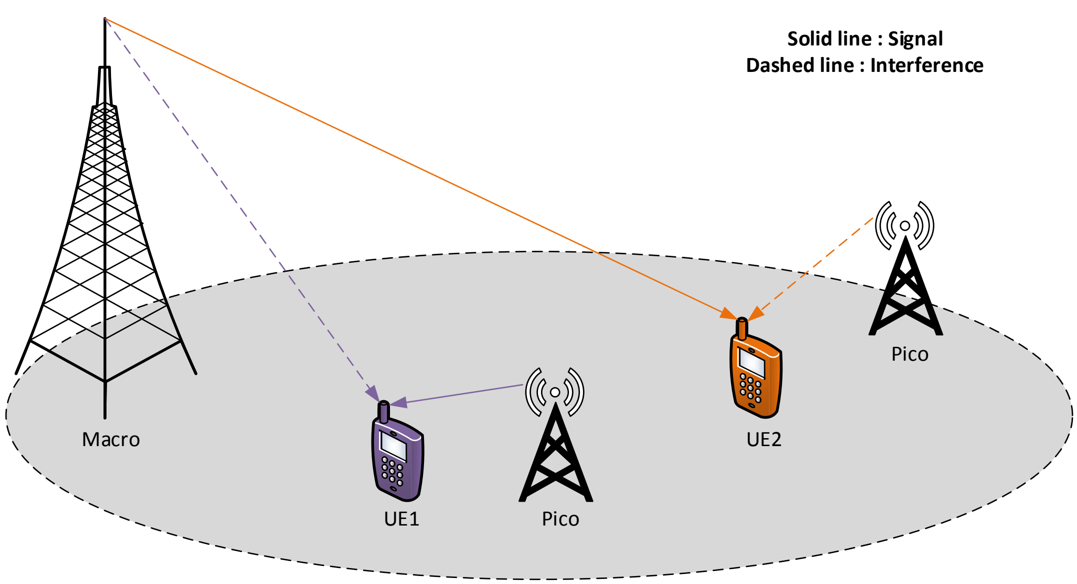


Figure 2.6: Small cell deployment: downlink interference

Furthermore, the uplink interference would also be strong. As illustrated in Figure 2.7, UE2 is assigned to MBS. However, in order for the uplink signal to be detectable at MBS, UE2 should transmit at relatively high power, which results in strong uplink interference at PBS. Hence, the uplink interference would become critical when a cell edge user is assigned to the MBS. In this case, its transmitted signal causes significant uplink interference in small cells.

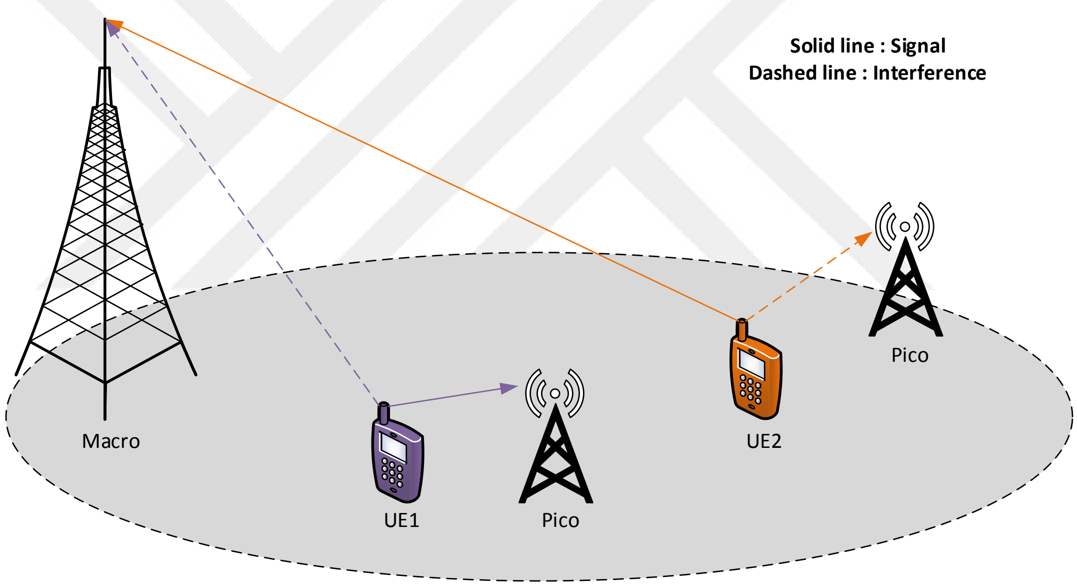


Figure 2.7: Small cell deployment: uplink interference

In this work, we proposed a completely orthogonal inter-tier and inter-cell resource allocation which completely eliminates any interference coordination concern. Instead, the focus of this work is to investigate the benefit of dynamic resource allocations in dynamically changing traffic load over static allocation strategies. Definitely, the static allocation methods are less complex and more favorable in static environments. However, we will show that in real world scenarios, where the fluctuation in the number of users for different hours is inevitable, static resource allocation results in a very poor performance of small cell deployment.

2.4.4 Energy Consumption

Although deploying small cells is a promising solution for increasing capacity of the wireless networks, the energy aspect of them is still a big challenge [36,37]. By reducing the user-AP distances, small cells could serve the users by significantly less transmit power than macro cell. Thus it could possibly reduce the total energy consumption of the network. However, in addition to transmit power, each SBS consumes a fixed amount of power, for keeping ON radios, cooling, etc. Therefore, small cells could have both positive and negative effects on network energy consumption. In dense deployments, small cells collectively consume a considerable amount of fixed energy which reduces energy efficiency of the network. In such scenarios, the problem of energy efficient deployment of HetNets becomes more critical. As a solution, turning small cells to Idle state, when its serving traffic drops below a certain threshold, can be considered.

In this approach, which is studied in this thesis, the dynamic activity control of each individual small cell, deployed by operator is considered. Specifically, each small cell reports its serving traffic to MBS and accordingly MBS decides about the efficient state of the small cell. Nevertheless, the required information for a switching decision would be more than serving traffic. For instance, the available network resources and the state of neighbouring small cells could help for more precise decision.

In the following chapter, the energy efficiency challenge will be studied and a dynamic activation strategy will be proposed. Moreover, to mitigate interference the resources will be partitioned between tiers and cells. Finally, an optimization platform will be introduced to address the efficient management of HetNets.

Chapter 3

Dynamic Activity Management Strategy

In this chapter we will first introduce our system model. Next the optimization problem will be introduced and at the end spacial case analysis of the problem are analytically studied.

3.1 System Model

3.1.1 User Association and Biasing

In this study, both inter-tier and intra-tier resource allocation is performed according to the received SNR at each user, meaning that a user would be assigned to macro tier if its received SNR from MBS is higher than all the SBSs. Otherwise it will be associated to a small cell which provides highest SNR among all the small cells. In case of biasing, a user will be connected to the BS which provides highest SNR weighted by its bias factor.

3.1.2 Dynamic State Switching

As it is introduced in the literature [20], switching SBS to Idle state during the off-peak hours is a possible solution for saving energy in small cell deployments. In this study the dynamic switching between Active and Idle states and its effect on the price of certain performance metrics is studied. While in Idle state BSs consume less energy for keep listening to (but not transmitting) signals, in Active state they consume a large amount of energy for air conditioning, signal processing unit, power amplifier unit, etc. Therefore, although they keep consuming energy in Idle state, due to the great difference between the consumed energy in Active and Idle states, it is more energy efficient to push SBSs to Idle state in off-peak hours of traffic.

3.1.3 User Distribution Model

In this work, users are generated according to two independent uniform distribution. The first uniform distribution is over the Macro cell and the second one is over small cell area. This model, which is known as HotSpot model, could well capture the characteristics of HetNets where SBSs are mainly deployed in a more crowded region,. Furthermore, in order to have a good match with real world small cell deployments, the densities of both distributions change as a function of time in a day-long duration. A macro cell sector with three HotSpot regions at the cell edge is depicted in Figure 3.1.

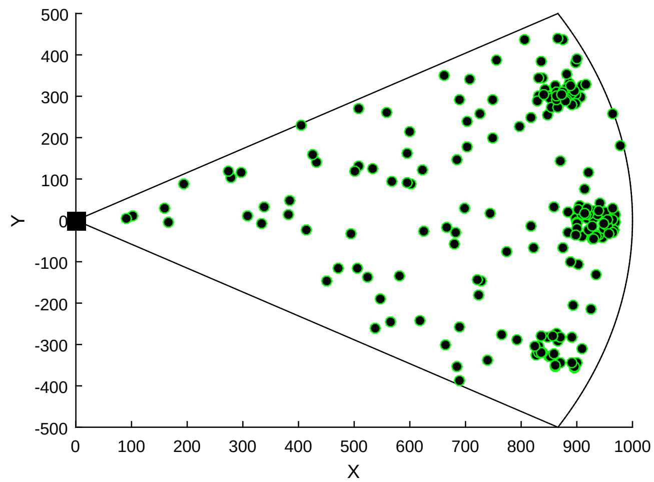


Figure 3.1: A macro cell with 3 HotSpot regions

3.2 Problem Statement and Solution

As mentioned earlier, the problems of utility maximization and Active/Idle switching have been studied in the literature. However, in this work we study the combined problem, which thoroughly captures the price of an specific metric in terms of energy. The metrics that we will study in this paper are the network sum rate and 10percent rate, which effectively addresses the degree of fairness of rate distribution in the network. Accordingly, we define the problem of energy-efficient utility-optimum 2-tier HetNet as follows:

$$\begin{aligned} max \qquad & \sum_{n=1}^{N} U_n(r_n) - \beta \sum_{k=1}^{K} E_k \\ s.t \quad & \sum_{n=1}^{N} RS_n = RS_T, \end{aligned} \tag{3.1}$$

where r_n is the data rate and $U(r_n)$ is the utility experienced by user n and N is the total number of users in the system. E_k is the energy consumed by kth BS and K is the number of BSs in the system. Here β stands for the relative price of energy in the studied environment. RS_n and RS_T correspond to the resource share of nth user and the total available resource in the system, respectively. Finally, r_n is given by the Shannon capacity formula,

$$r_n = W_n log(1 + \frac{P_n}{N_0 W_n}) \tag{3.2}$$

where W_n and P_n the allocated bandwidth and received power of user n, respectively, and N_0 is the noise power spectral density. There are a broad range of utility functions defined in the literature. Authors in [38] and [39] use a linear utility function while a piecewise utility function is employed in [40]. Linear and piecewise linear utility functions give higher rewards to the users who are already rich in the environment. However, another utility function which is known to guarantee proportional fairness in the system is the logarithmic utility function [41,42]. The basic idea behind using logarithmic utility function is that, due to its concavity, it cares more about the penalized users in the system, compared to linear utility functions. This simple but important feature of the logarithmic function make it a good feat for capturing fairness, where the goal is to provide an acceptable quality of experience for most of the users. This goal indeed cannot be achieved when linear utility function is employed. Accordingly, the energy-efficient proportional fair optimization problem for a 2-tier HetNet can be written as

$$\begin{aligned} max \qquad & \sum_{n=1}^{N} ln(r_n) - \beta \sum_{k=1}^{K} E_k \\ s.t \quad & \sum_{n=1}^{N} W_n = W_T, \end{aligned} \tag{3.3}$$

where W_T is the total available spectrum in the network.

3.2.1 Problem Solution and Discussions

Since $ln(.)$ is a strictly concave function in the range of $(0, \infty)$, we can define $f_1(\overline{r})$ and $f_2(\overline{r})$ such as

$$\begin{aligned} f_1(\overline{r}) = ln(r_1) \Rightarrow f_1(a\overline{r}_1 + (1-a)\overline{r}_2) > af_1(\overline{r}_1) + (1-a)f_1(\overline{r}_2) \\ f_2(\overline{r}) = ln(r_2) \Rightarrow f_2(a\overline{r}_1 + (1-a)\overline{r}_2) > af_2(\overline{r}_1) + (1-a)f_2(\overline{r}_2) \end{aligned} \tag{3.4}$$

where $\overline{r} = (r_1, r_2, ..., r_N)$ and $0 < a < 1$. Now, by defining $f(\overline{r}) = f_1(\overline{r}) + f_2(\overline{r})$, we have

$$\begin{aligned} f(a\overline{r}_1 + (1-a)\overline{r}_2) &= f_1(a\overline{r}_1 + (1-a)\overline{r}_2) + f_2(a\overline{r}_1 + (1-a)\overline{r}_2) \\ &> af_1(\overline{r}_1) + (1-a)f_1(\overline{r}_2) + af_2(\overline{r}_1) + (1-a)f_2(\overline{r}_2) \\ &= a(f_1(\overline{r}_1) + f_2(\overline{r}_1)) + (1-a)(f_1(\overline{r}_2) + f_2(\overline{r}_2)) \\ &= af(\overline{r}_1) + (1-a)f(\overline{r}_2). \end{aligned} \tag{3.5}$$

Therefore $f(\overline{r})$, which is the summation of logarithmic functions, is also a strictly concave function. Accordingly the optimization problem (3.3) is a concave problem with respect to r_n. On the other hand, r_n is a concave function with respect to W_n [43]. Moreover, any concave function of a concave function is still concave [44]. Consequently the optimization problem (3.3) is a concave problem with respect to W_n and, therefore, has a single global optimum. Considering K BSs inside the network, there are 2^K distinct concave problems that need to be solved. After solving the set of all possible optimization problems there are 2^K solutions, each of which associates with a specific BSs state vector. The BSs state vector is a binary vector the length of which is equal to the number of BSs in the network. Finally, the optimum solution of the problem is the one associated with the maximum objective between all 2^K possible objectives.

Moreover, although in Active state they consume energy both in radio unit and electronic circuits, SBSs consume a small percentage of electronic circuits to keep listening to control signals. Therefore, keeping SBSs in Idle state seems to be more energy efficient. However, the achievable sum utility improvement by activating more SBSs pushes the system to keep more SBSs in Active state. Accordingly, the optimum solution of the problem would make a trade-off between sum utility improvement and the network energy consumption.

Furthermore, we introduce another parameter to the problem, β, which controls the compatibility of the first and second terms in the objective function as well as the relative price of the energy of the studied environment. Essentially, the larger β stands for the greater price of the energy and the smaller β corresponds to the lower energy price. Therefore, it is expected that dynamic Active/Idle strategy pushes more small cells to Idle state as the value of β gets larger. On the other hand, for a given β it is expected that in the small cell peak hours the dynamic strategy pushes more small cells to Active state than off-peak hours.

3.2.2 High SNR Analysis

Here, we study how the proportional fair scheduler will divide the total bandwidth between different users in high SNR regime, which is a valid regime in our system model. In high SNR regime, the data rate at user i can be written as

$$\begin{aligned} R_i &= W_i log(\frac{S_i}{N_0 W_i}) \\ &= W_i log(\frac{S'_i}{W_i}). \end{aligned} \tag{3.6}$$

Hence, for a given BS activity vector, the optimization problem is

$$\begin{aligned} max \qquad & \sum_{i=1}^{N} ln(r_i) \\ s.t. \quad & \sum_{i=1}^{N} W_i = W_T \\ & W_i > 0 \end{aligned} \tag{3.7}$$

or equivalently,

$$\begin{aligned} max \qquad & \sum_{i=1}^{N} lnW_i + ln(log\frac{S'_i}{W_i}) \\ s.t. \quad & \sum_{i=1}^{N} W_i = W_T \\ & W_i > 0. \end{aligned} \tag{3.8}$$

For solving this optimization problem, the Lagrange Multipliers method is employed. The Lagrange function for this problem is

$$f(W_1, W_2, ..., W_N, \lambda) = \sum_{i=1}^{N} \left(lnW_i + ln\left(log\frac{S'_i}{W_i} \right) \right) + \lambda \left(\sum_{i=1}^{N} W_i - W_T \right) \tag{3.9}$$

and the Lagrange conditions are

$$\left(\frac{\partial f}{\partial W_1}, \frac{\partial f}{\partial W_2}, ..., \frac{\partial f}{\partial W_N}, \frac{\partial f}{\partial \lambda} \right) = 0 \tag{3.10}$$

Therefore, the system of equations for finding the optimum solution turns out to be

$$\begin{cases} \dfrac{1}{W_i}\left(1-\dfrac{1}{log\frac{S'_i}{W_i}}\right)+\lambda=0, \quad i=1,2,...,N \\ \displaystyle\sum_{i=1}^{N} W_i - W_T = 0 \end{cases} \tag{3.11}$$

which is a nonlinear system of equations could be solved by employing numerical methods [45]. Nevertheless, to have a perspective about the fundamental properties of the optimization problem, in the following we will compare the allocated bandwidth to two different users with different received powers in the network. According to the system of nonlinear equations, the following equalities are obtained,

$$\begin{aligned} &\frac{\partial f}{\partial W_i} = 0 \Rightarrow \\ &\frac{1}{W_i}\left(1-\frac{1}{log\frac{S'_i}{W_i}}\right)+\lambda = 0 \Rightarrow \\ &\lambda W_i = \frac{1}{log\frac{S'_i}{W_i}} - 1 \Rightarrow \\ &\lambda W_i log\frac{S'_i}{W_i} = 1 - log\frac{S'_i}{W_i} \Rightarrow \\ &\lambda W_i log\frac{S'_i}{W_i} = log\frac{2W_i}{S'_i} \Rightarrow \\ &-\lambda W_i log\frac{W_i}{S'_i} = log\frac{2W_i}{S'_i}. \end{aligned} \tag{3.12}$$

Now, for users i and j the following equality should hold,

$$\frac{-\lambda W_i log\frac{W_i}{S'_i}}{-\lambda W_j log\frac{W_j}{S'_j}} = \frac{log\frac{2W_i}{S'_i}}{log\frac{2W_j}{S'_j}}. \tag{3.13}$$

Without loss of generality, assume user i receives stronger signal than user j. Therefore, there exist an $\alpha > 1$ such that $S'_i = \alpha S'_j$. Then the equality (3.11) can be rewritten as

$$\frac{W_i log\frac{W_i}{\alpha S'_j}}{W_j log\frac{W_j}{S'_j}} = \frac{log\frac{2W_i}{\alpha S'_j}}{log\frac{2W_j}{S'_j}}. \tag{3.14}$$

Now assume that the proportional fair scheduler assigns less spectrum to user i. Hence, there should be a $\gamma < 1$ such that $W_i = \gamma W_j$. Thus, (3.12) is rewritten as

$$\begin{aligned}
&\frac{\gamma W_j log\frac{\gamma W_j}{\alpha S'_j}}{W_j log\frac{W_j}{S'_j}} = \frac{log\frac{2\gamma W_j}{\alpha S'_j}}{log\frac{2W_j}{S'_j}} \Rightarrow \\
&\frac{\gamma\left(log\frac{W_j}{S'_j} + log\frac{\gamma}{\alpha}\right)}{log\frac{W_j}{S'_j}} = \frac{log\frac{2W_j}{S'_j} + log\frac{\gamma}{\alpha}}{log\frac{2W_j}{S'_j}} \Rightarrow \\
&\gamma\left(1 + \frac{log\frac{\gamma}{\alpha}}{log\frac{W_j}{S'_j}}\right) = 1 + \frac{log\frac{\gamma}{\alpha}}{log\frac{2W_j}{S'_j}}
\end{aligned} \tag{3.15}$$

or equivalently,

$$\gamma + \frac{\gamma log\frac{\gamma}{\alpha}}{log\frac{W_j}{S'_j}} = 1 + \frac{log\frac{\gamma}{\alpha}}{log\frac{2W_j}{S'_j}}. \tag{3.16}$$

Since $\gamma < 1$, the following inequalities should hold

$$\begin{aligned}
&\frac{\gamma log\frac{\gamma}{\alpha}}{log\frac{W_j}{S'_j}} > \frac{log\frac{\gamma}{\alpha}}{log\frac{2W_j}{S'_j}} \Rightarrow \\
&\frac{\gamma}{log\frac{W_j}{S'_j}} > \frac{1}{log\frac{2W_j}{S'_j}} \Rightarrow \\
&\left(\frac{1}{\gamma} - 1\right) log\frac{W_j}{S'_j} > 1 \Rightarrow \\
&log(W_j) - log(S'_j) > \frac{1}{\frac{1}{\gamma} - 1}
\end{aligned} \tag{3.17}$$

According to the definition, γ takes value in the range of $(0,1)$. Thus, the RHS of the last inequality takes value in the range of $(0,\infty)$. Therefore, the inequality can be rewriten as

$$\begin{aligned} &log(W_j) - log(S'_j) > 0 \Rightarrow \\ &W_j > S'_j \end{aligned} \tag{3.18}$$

Apparently, the validity of inequality (3.16) depends on the system parameters, such as available spectrum for each user and their received powers. In our simulation platform, the total available spectrum (which is the maximum bandwidth share could be assigned to a user) is 10^8Hz. On the other hand, the minimum received power in the cell with the radius of 1000m, which is experienced by the users on the macro cell edge, is

$$\begin{aligned} S_{min} &= P_T + G_a - PL_{max} \\ &= 46 + 14 - 128.1 - 37.6log_{10}(1_{km}) \\ &= -68.1dBm, \end{aligned} \tag{3.19}$$

where P_T is the transmit power, G_a is the BS antenna gain and PL_{max} corresponds to the maximum path loss [46]. On the other hand, the noise spectral density is written as

$$\begin{aligned} N_0 &= kT \\ &= 1.38 \times 10^{-23} \times 298 \times 10^3 mW \\ &= 10^{-17.4} mW. \end{aligned} \tag{3.20}$$

Therefore,

$$\begin{aligned} S'_{min} &= \frac{10^{-6.8}}{10^{-17.4}} \\ &= 10^{10.6} \end{aligned} \tag{3.21}$$

which reveals that the minimum value of S'_j is greater then the largest value of W_j. Hence, the inequality (3.16) will not be valid in our system model. This implies that our earlier assumption on γ is not valid in our model. Consequently, by contradiction, γ takes value in the range of $(1, \infty)$. This implies that, in our system model with proportional fair allocation, if a given user receives stronger signal it will be assigned larger spectrum.

To solve the optimization problem (3.3), Branch-And-Reduce Optimization Navigator (BARON) is employed [47]. BARON is a toolbox for finding global optimum of algebraic nonlinear problems. We used this toolbox in MATLAB in order to find the global optimum of the optimization problem (3.3), the existence of which was proved in section 3.2.1.

Chapter 4

Numerical Results

In this chapter, we will present the network topology we consider, the simulation platform and the simulation results.

4.1 Network Topology

As depicted in Figures 4.1 - 4.3, a three-sector Macro cell is considered. In the cell edge of each sector, HotSpot regions ares considered. Further, a Pico BS (PBS) is located at the center of each HotSpot region.

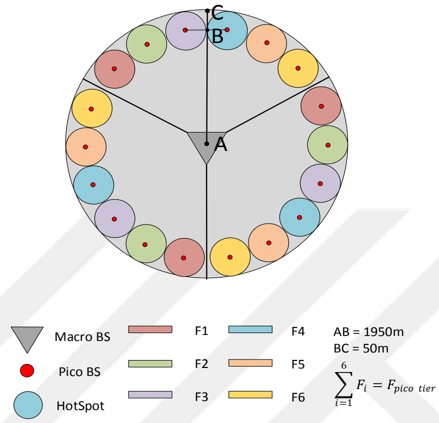


Figure 4.1: Network topology, Macro cell radius 500m.

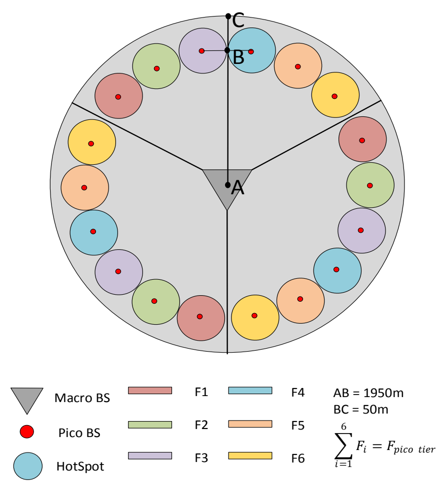


Figure 4.2: Network topology, Macro cell radius 1000m.

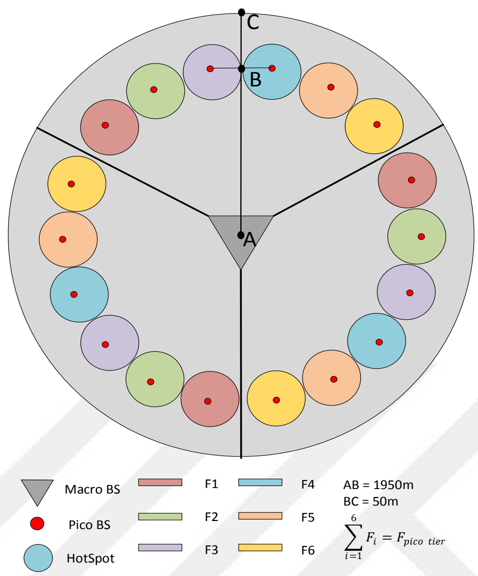


Figure 4.3: Network topology, Macro cell radius 2000m.

4.2 Simulation Model

4.2.1 User Distribution

In the simulation model, where 6 HotSpot regions are considered at the cell edge of each sector in the Macro cell, the users are generated according to seven different uniform distributions for each sector,

- One over the entire Macro cell, with average number of users of $\overline{N}_m$,
- And six others over HotSpot regions, with the total average number of users of $\overline{N}_h$.

In addition, in order to capture the fluctuations of users in the network, the numbers of fluctuated users are drawn from another two zero-mean uniform distributions, n_m and n_h, which are given by

- For Macro cell area, n_m takes values in the range of $[-\sigma_m \overline{N}_m, \sigma_m \overline{N}_m]$,
- For HotSpot area, n_h takes values in the range of $[-\sigma_h \overline{N}_h, \sigma_h \overline{N}_h]$,

where σ_m and σ_h are the maximum deviation of the number of users from its mean value. Therefore, the total number of users are,

$$\begin{aligned} N_m &= \overline{N}_m + n_m \\ N_h &= \overline{N}_h + n_h \end{aligned} \tag{4.1}$$

where N_m and N_h are the number of users in macro cell and HotSpot region. In the setting considered in this thesis $\overline{N}_m$ and $\overline{N}_h$ change over time, as are indicated in the following vectors,

- $\overline{N}_m = [197 \quad 170 \quad 140 \quad 110 \quad 80 \quad 50 \quad 20 \quad 5 \quad 5]$,
- $\overline{N}_h = [1 \quad 10 \quad 20 \quad 30 \quad 40 \quad 50 \quad 60 \quad 65 \quad 65]$.

Further, σ_m and σ_h are 0.2 and 0.4, respectively. The variation of average number of users in macro and pico tiers are illustrated in Figure 4.4.

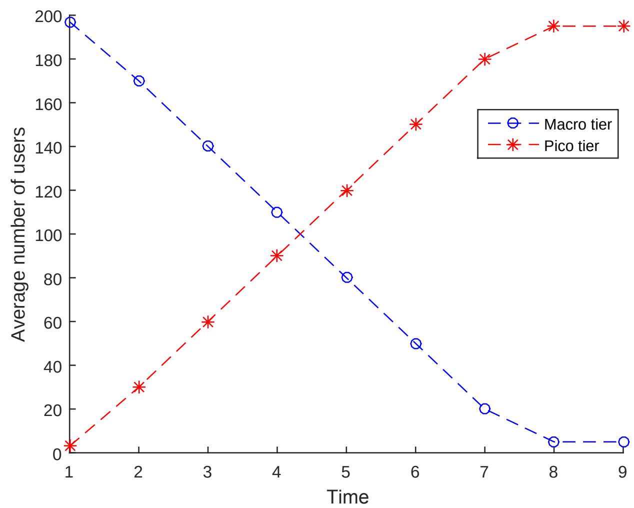


Figure 4.4: Average number of users

4.2.2 Channel Loss Model

For the purpose of our simulation, the simplified path loss model together with log-normal shadowing are considered [43]. The channel loss model parameters are given in Table 4.1.

	Macro cell	Pico cell
Path loss	128.1 + 37.6log(R[km])	140.7 + 36.7log(R[km])
Shadowing	log-normal, std=8dB	log-normal, std=10dB

Table 4.1: Channel loss model

4.2.3 Power Consumption Model for BSs and Biasing

In our simulation, we follow the power consumption model as described in [48]. Specifically, in Active mode, BSs consume P_{Active} amount of power and transmit at the maximum power, regardless of the serving load, and in Idle mode they consume P_{Idle} amount of power. The power specifications in our model are summarized in Table 4.2.

	Macro BS	Pico BS
$P_{Acvtive}$	390W	9W
P_{Idle}	NA	0.2W
Transmit power	46dBm	30dBm

Table 4.2: BSs power consumption model

4.2.4 Dynamic Activation Model

In order to save energy, the PBSs would be placed to Idle state if their serving traffic drops below a threshold. In our model, the threshold is not predefined and it is determined by the optimization problem. More specifically, the state of each PBS, Active or Idle, is one of the outputs of the optimization problem. To find the optimum state of them, we study all possible combinations of the states of small cells and choose the state which provides highest objective. Although it is not possible to estimate the optimum state of each PBS before running the optimization problem, the number of users in each Pico cell and the relative price of energy in the environment are the most important factors for making decision about their states. As it was mentioned, since the consumed power in Idle state is much smaller than Active state, the optimization problem pushes some Pico BSs to Idle state if the associated HotSpot is not dense enough.

4.2.5 Bandwidth Allocation Model

We consider two resource allocation policies:

- Static bandwidth allocation, in which both inter-tier and inter-cell allocations are completely orthogonal and static over time.

- Dynamic bandwidth allocation, in which both inter-tier and inter-cell allocations are again completely orthogonal but dynamic over time.

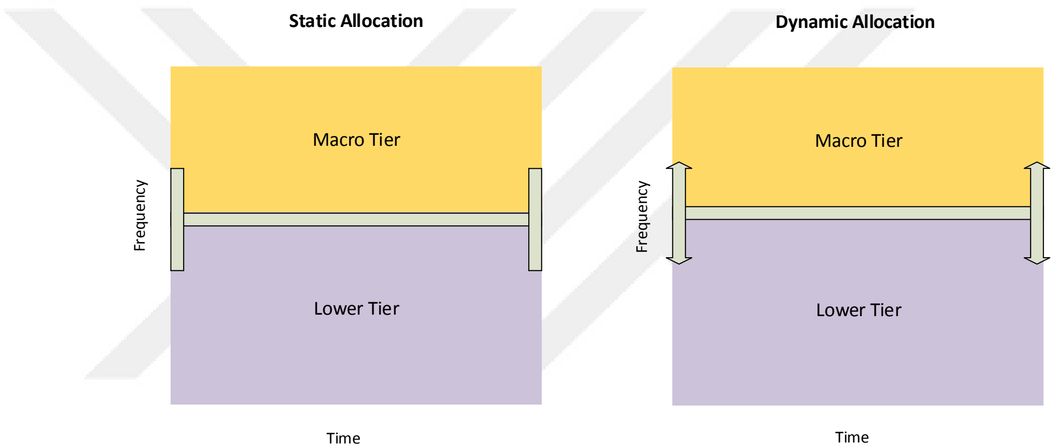


Figure 4.5: Resource allocation policies

4.3 Simulation Results

Simulation scenarios are,

- *Macro Only*, in which picos are all in Idle state and the all the users are served by macro.

- *Picos Active with α percent RS*, in which all the picos are Active and are collectively using α percent of resources. Macro cell in these strategies uses $(100 - \alpha)$ percent of resources.

- *Dynamic Bandwidth Allocation Dynamic Activation (DBADA)*, in which the optimum state of each pico (Active or Idle) is dynamically determined.

Further, inter-tier and intra-tier resource allocations are completely orthogonal and are dynamically adjusted according to traffic variations.

We consider three resource allocation policies:

- Proportional Fair Scheduling (PFS), where the resources are allocated such that the sum of logarithm of data rates be maximized.
- Sum Rate Maximization (SRM), where resources are allocated such that the sum of data rates be maximized.
- Equal Allocation (EA), where the resources are allocated equally between the users.

The simulation results for macro cell radiuses of 500m, 1000m and 2000m are given in the following figures.

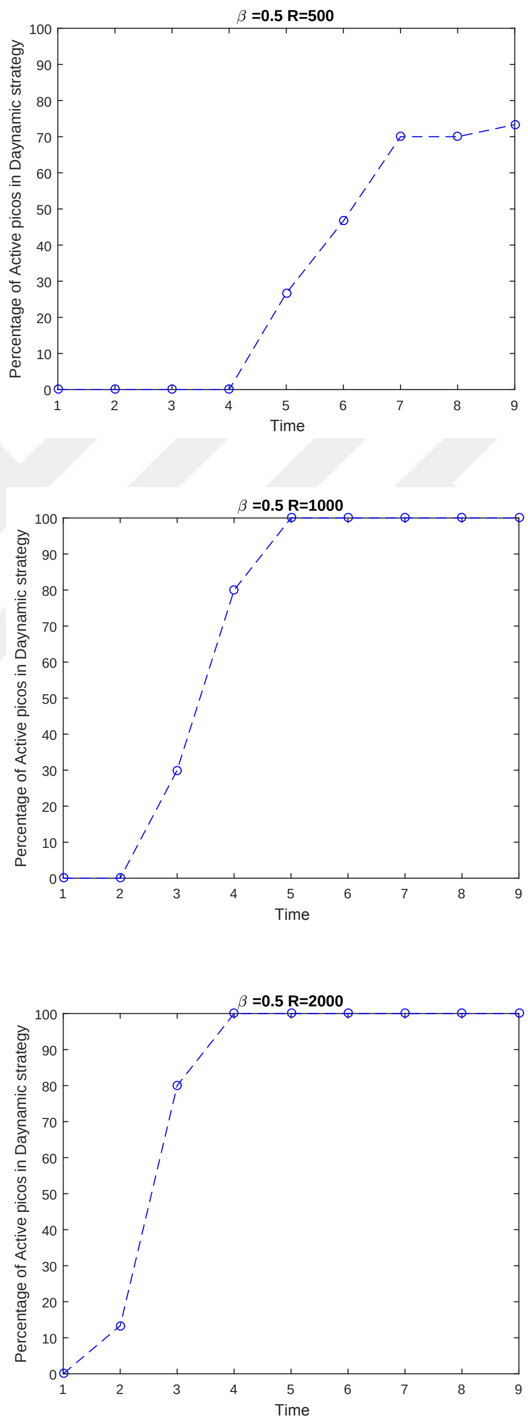


Figure 4.6: Average number of Active picos

As it is depicted in Figure 4.6, the average number of Active picos in dynamic activation strategy increases as the traffic load of HotSpot regions grows. Regardless of the macro cell size, in off-peak hours of traffic of HotSpot regions, dynamic activation strategy prefers all pico cells to be in Idle state. Furthermore, as the cell radius increases, for a given hour, the dynamic activation strategy pushes more picos to Active state. This is in line with intuition that the deployment of small cells in the cell edge of larger macro cells is more beneficial, due to the poor coverage of macro cell in cell edge. Interestingly, in $R = 500m$ and even in peak hours of traffic of HotSpot region, the dynamic activation strategy only prefers a subset of all pico cells to be in Active state. This effectively means that deploying 6 pico cells, in $R = 500m$ macro cell, is more than enough. However, in $R = 1000m$ and $R = 2000m$ all of the pico cells are utilized in peak hours.

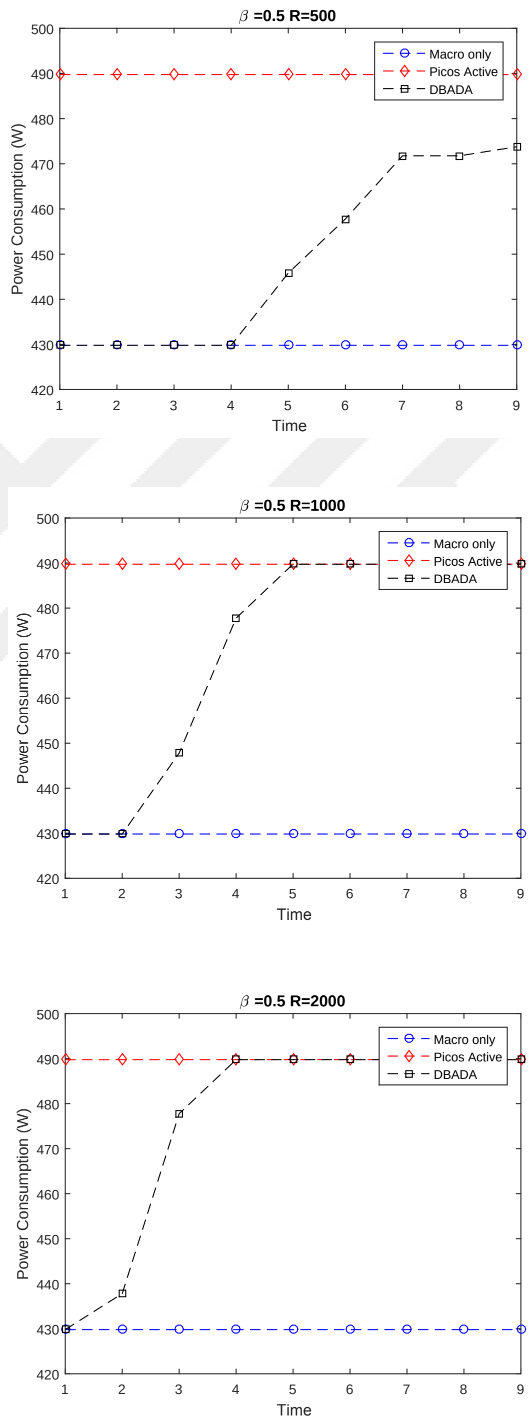


Figure 4.7: Network power consumption

Figure 4.7, The power consumption for different macro cell radiuses, reveal that as the cell size grows the consumed power by BSs also grows in the DBADA strategy. This fact is parallel to intuition; because as the cell size increases the cell edge experience gets worse. This happens due to the growth in the average UE-AP distance in the large cells. Therefore, since DBADA strategy pushes pico cells to Active state if they can deliver enough benefits in terms of both network utility and power consumption, in larger macro cells it would activate small cells more frequently than in smaller macro cells.

In the following figures, we compare the performance of the following strategies:

- *Macro only with PFS*, where all the small cells are always in idle state and all the users are served by macro cell. Inter-user bandwidth allocation is adjusted such that the proportional fairness constraint is satisfied.
- *Picos Active with α% BW and PFS*, where all the small cells are always in Active state. The inter-tier and inter-cell bandwidth allocations are fixed and same for all the hours, such that small cells collectively receive $\alpha\%$ and macro cell receives $(100-\alpha)\%$ of bandwidth. The allocated bandwidth to small cell tier are equally divided between small cells. Inside each cell, the inter-user resource allocation is adjusted such that the proportional fairness constraint is satisfied.
- *DBADA with PFS*, where the optimal state of each small cell, Active or Idle, is determined dynamically. The inter-tier, inter-cell and inter-user resource allocations satisfy proportional fairness constraint.

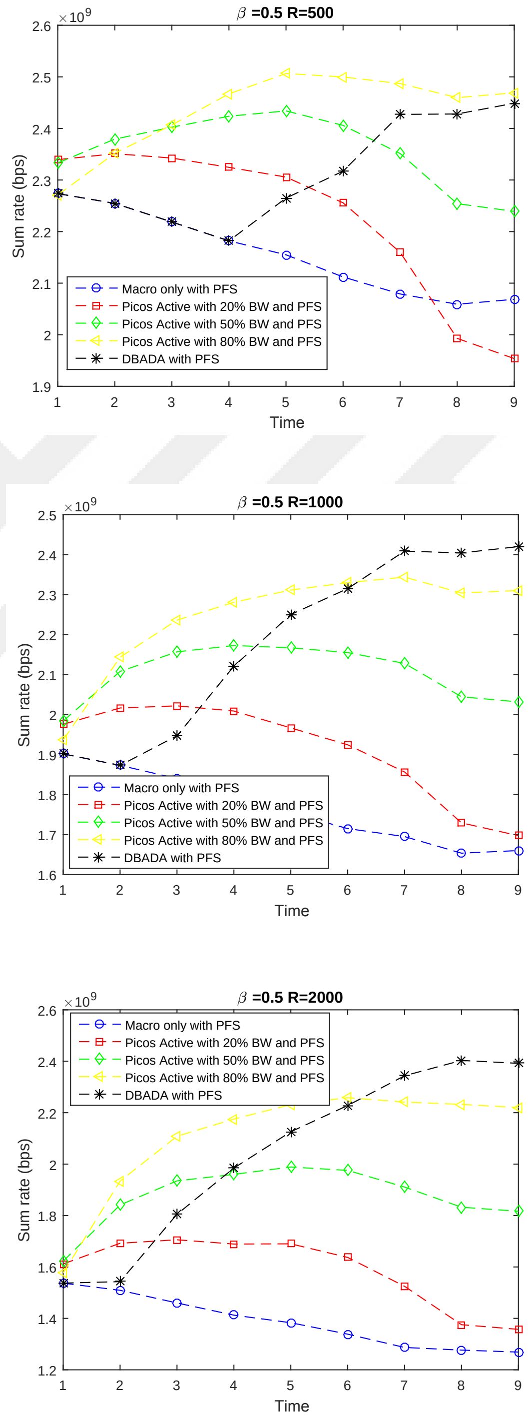


Figure 4.8: Sum rate

As it is depicted in Figure 4.8, the maximum sum rate strategy is the one which allocates more bandwidth to pico tier. This fact is intuitively true since most of the pico cell user experience stronger signals than macro cell users. Hence assigning them greater portion of resources would result in higher network sum rate. Nevertheless, DBADA with PFS strategy, which is known to achieve global proportional fairness, has the best performance only in peak hours when even Picos Active with 80% BW fails to maximize the network sum rate. The intuition behind this fact is that in peak hours, when most of users are located in pico cells, the maximum sum rate and maximum sum utility techniques introduce the same allocated bandwidth between tiers.

On the other hand, in Figure 4.8 we can see that as the macro cell radius increases, the sum rate of both Macro only and Picos Active scenarios drop in peak hours, due to the growth in average UE-AP distance. However, DBADA with PFS strategy experiences very little drop compared to the other strategies. This is because, the fixed inter-tier resource allocation does not only fail to adopt to different traffic variations but they also would not achieve the same performance in different macro cell sizes, since the average UE-AP distance would not experience the same changes in different tiers. Although the average distance would increase in macro tier, the pico tier average distance would remain almost the same. Accordingly, the fixed inter-tier resource partitioning policies wont result in the same performance, specially sum rate, in different macro cell sizes.

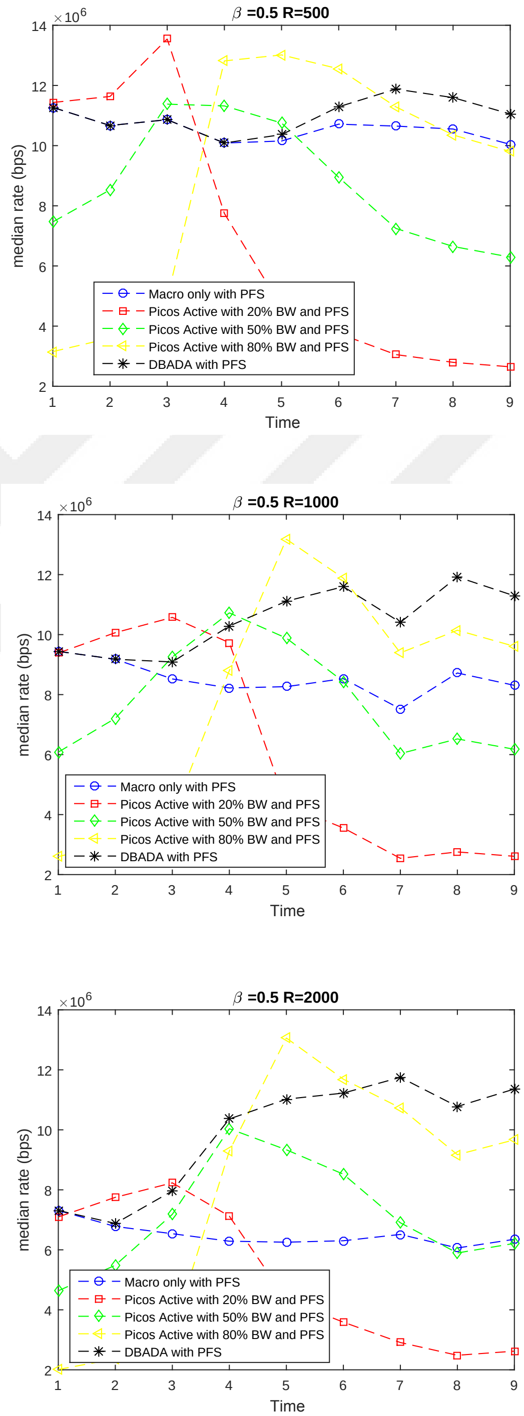


Figure 4.9: Median rate

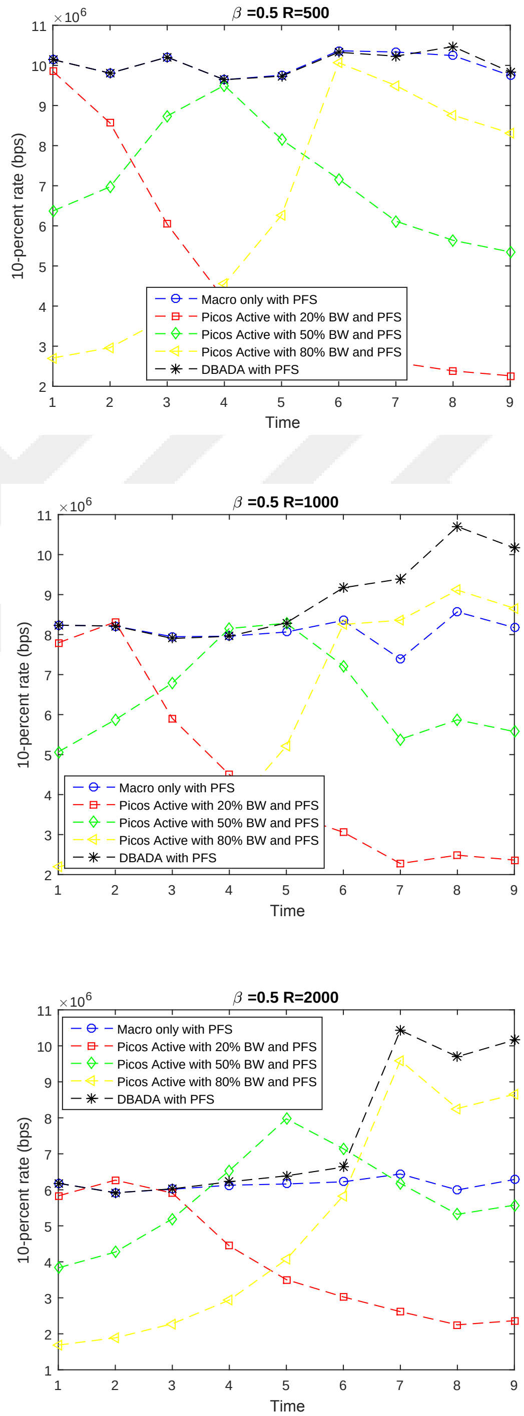


Figure 4.10: 10-percent rate

In median rate plot, Figure 4.9, the Macro only scenario could not maintain the same performance in peak hours, since as the traffic shifts toward pico cells the median user experiences weaker signal and lower data rate from MBS. On the other hand, pushing pico cells to Active state and assigning them a fixed amount of resources in all the hours results in a poor average performance. For instance, assigning pico tier 20% BW only shows a desirable performance in off-peak hours, while in median to peak hours of traffic it fails to maintain its off-peak hour performance. The same result is observed by assigning pico tier 50% and 80% of total BW, which only show a desirable performance in median and peak hours of traffic of HotSpot regions, respectively. However, DBADA with PFS maintains a desirable median rate performance in all hours, which is always better than Macro only scenario.

For 10-percent rate metric, which is the data rate that is guaranteed to be achieved by at least 90% of users, in Figure 4.10 we can see the same performance for different traffic variations in Macro only scenario, because the location of 10-percent users are almost the same in each hour and they are located at the cell edge. On the other hand, the Picos Active scenarios fails to adapt to different traffic variations and each of them performs well for a few hours. For instance, while assigning 20% BW to pico tier results in a high 10-percent rate in HotSpot off-peak hours, it is the worst scenario in HotSpot peak hours. Instead, Picos Active with 80% BW and PFS is the best strategy in peak hours. Nevertheless, DBADA with PFS has the most stable and highest-average performance over all strategies. Due to the global proportional fairness, which is guaranteed by this strategy, DBADA is able to achieve the highest fairness in the network.

On the other hand, as the cell size increases, the median and 10-percent rates of Macro only scenario in peak hours decrease, which is the result of the growth of average UE-AP distance. However, with deploying pico cells in the cell edge, the peak hour median and 10-percent rates could be well maintained.

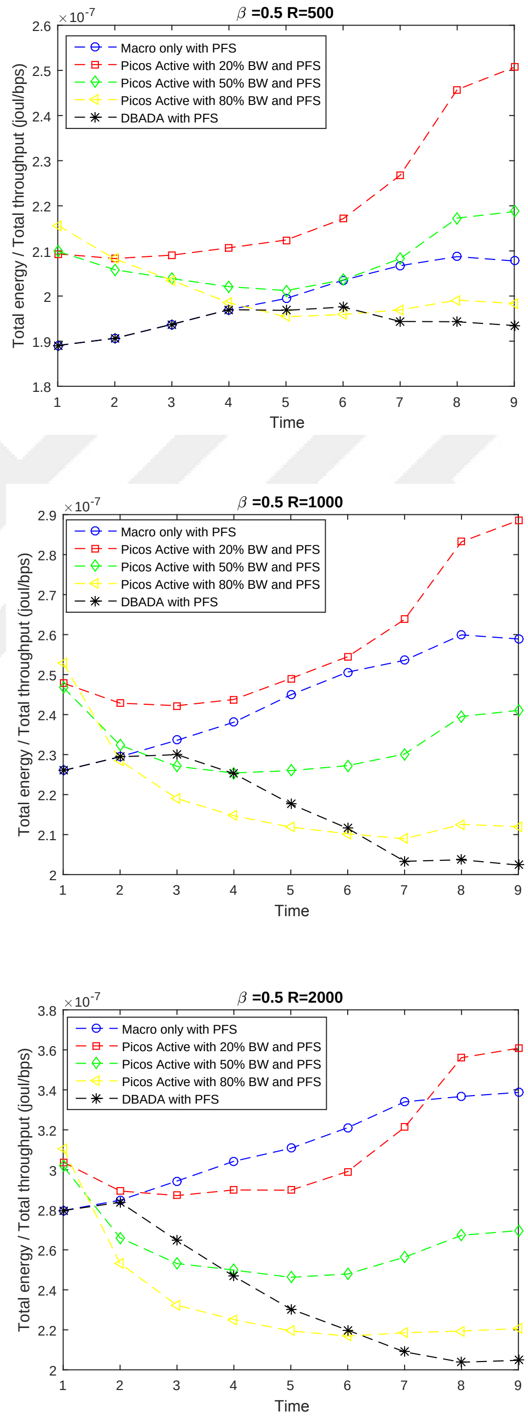


Figure 4.11: Energy per sum rate

In Figure 4.11, the energy per network sum rate is plotted for 9 hours of traffic and 3 different cell sizes. In macro only scenario the energy per sum rate increases as the traffic shifts toward HotSpot region, since the sum rate decreases in HotSpot peak hour for this scenario. Picos Active with 20% BW also shows poorer performance in peak hours. On the other hand, Picos Active with 80% BW, which performs well in peak hours, has a poor performance in off-peak hours. Therefore, either turning off the pico cells or turning them on with a fixed portion of resources fail to maintain a well performance over all the traffic variations. However, DBADA with PFS performs more stable and is able to achieve the minimum or close to minimum energy per sum rate in all the hours. Moreover, as the cell size increases, the gap between DBADA strategy and Macro only scenario increases. This observation could be well described by the poor cell edge coverage of macro cell in larger cells, which could be improved by COE deployment of small cells.

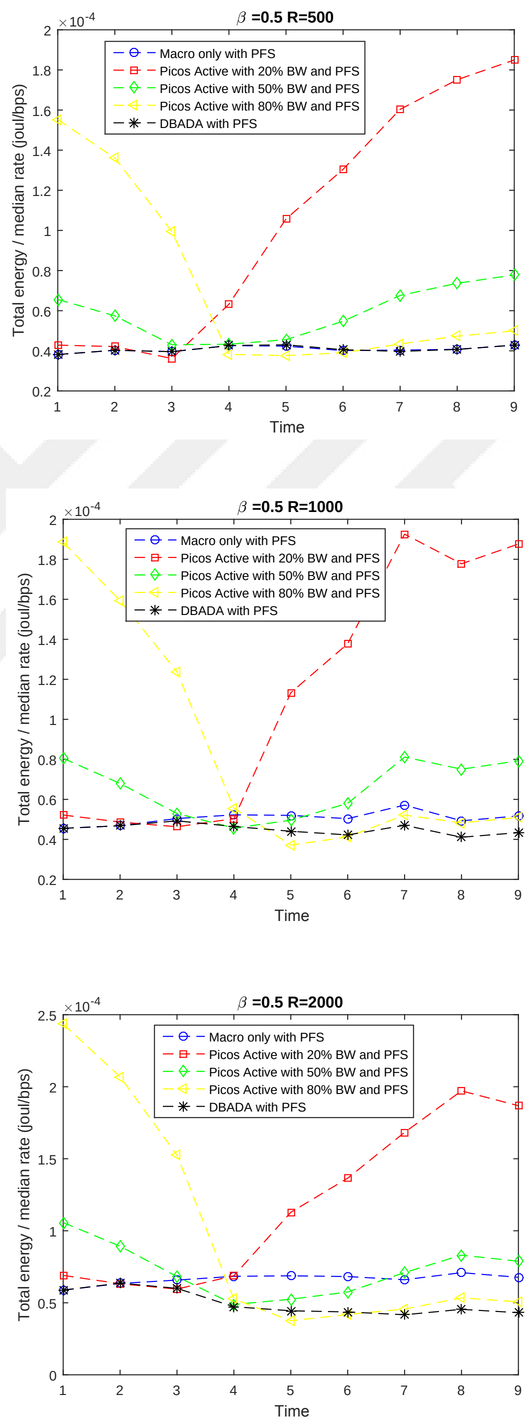


Figure 4.12: Energy per median rate

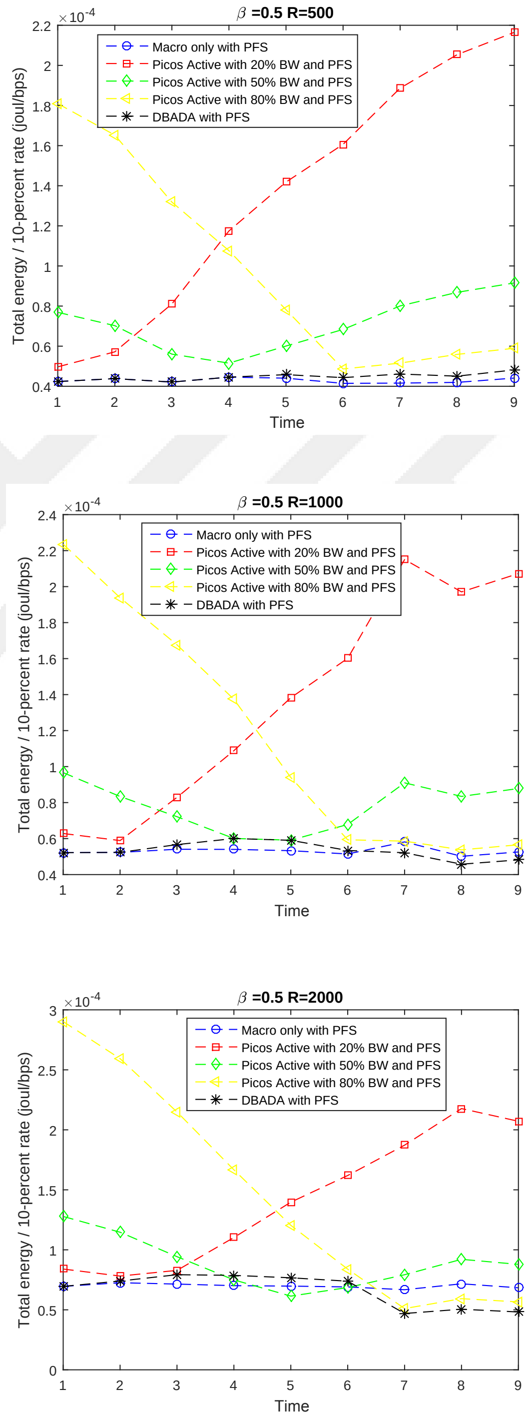


Figure 4.13: Energy per 10-percent rate

In Figure 4.12, it is shown that Picos Active with 20% and 80% BW can only maintain a desirable energy per median rate for a few hours. Picos Active with 50% BW is a more stable scenario but it has a moderate performance in all hours. On the other hand, specially in smaller cells, Macro only scenario has a better performance in terms of energy per median rate than Picos Active with fixed portion of BW. However, DBADA with PFS, performs better than Macro only scenario and at the same time maintains the minimum or close to minimum energy per median rate in all the hours.

The same observation is made in Figure 4.13, where the Picos Active scenarios fail to maintain their performance in all hours. Again, DBADA maintains the minimum or close to minimum energy per 10-percent rate in all the hours.

Furthermore, as it can be seen from Figures 4.12 and 4.13, The gap between DBADA strategy and macro only scenario increases in larger macro cells. Since in the larger macro cell the cell edge users has a poorer experience than smaller cells, when Macro only scenario is established. Therefore, it is expected that the COE deployment provides a better fairness improvement in larger cells.

In the following the averages, over 9 hours of traffic, of the discussed metrics are provided. In addition, to examine the maximum fairness for Macro only and Picos Active scenario, and compare it with DBADA with PFS strategy, the performance of these metrics are evaluated under equal resource allocation between users (the highest fairness) and their average performance are included in the following plots.

The abbreviations used in the figuers are summaraized in Table 4.3.

MOPFS	Macro only with PFS
MOEA	Macro only with EA
MOSRM	Macro only with SRM
PAα%PFS	Picos Active with α% BW and PFS
PAα%EA	Picos Active with α% BW and EA
PAα%SRM	Picos Active with α% BW and SRM
DBADA PFS	DBADA with PFS

Table 4.3: Abbreviations

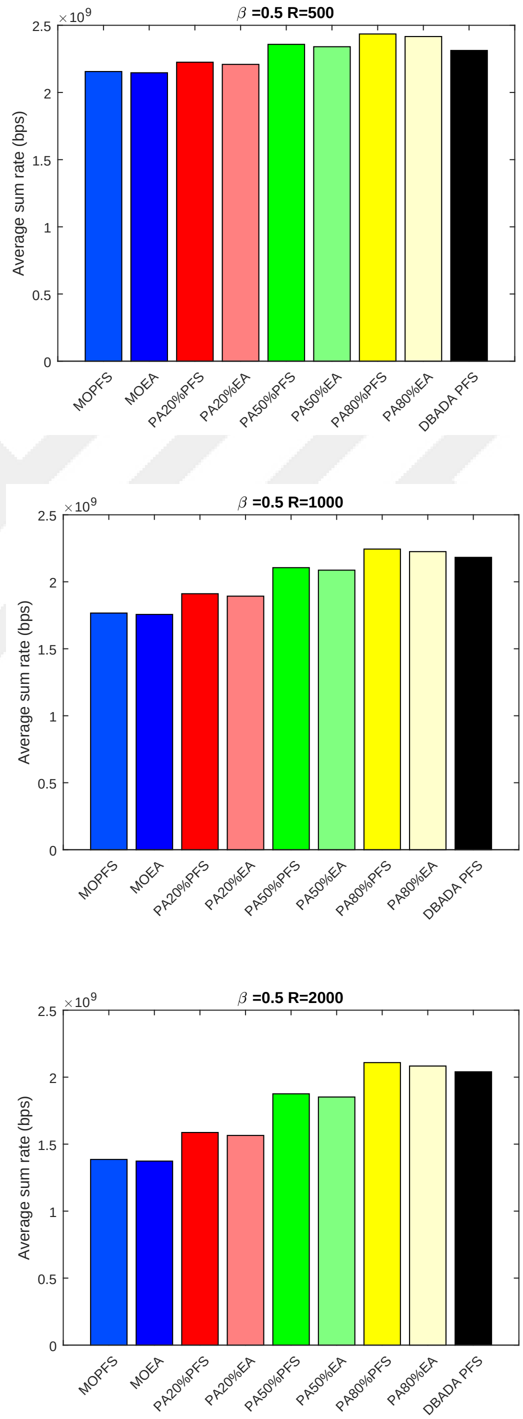
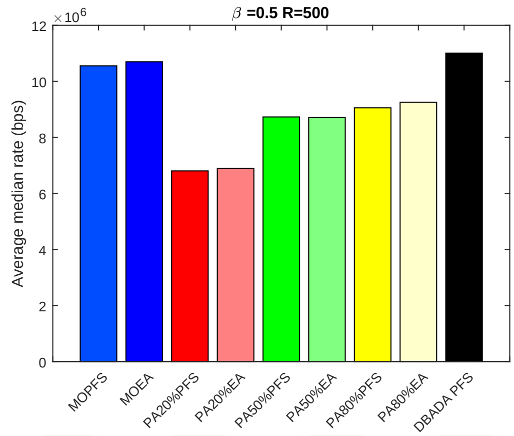
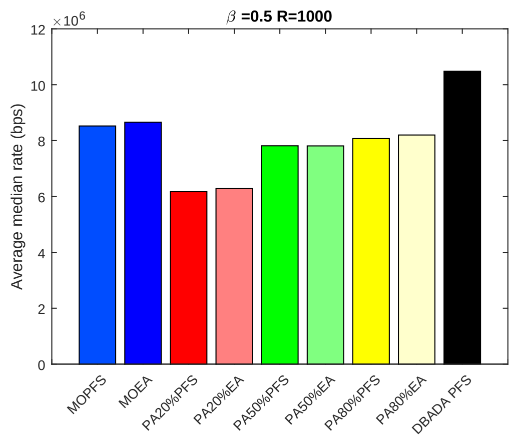


Figure 4.14: Average sum rate over all hours





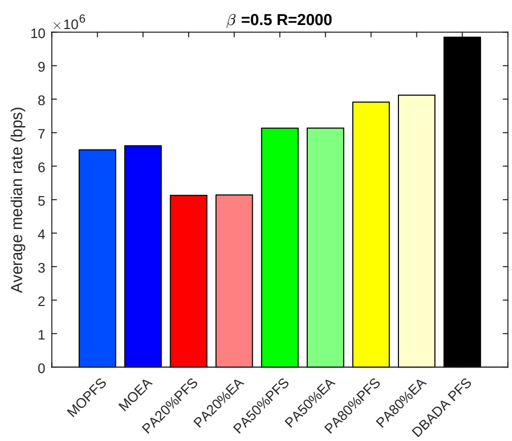


Figure 4.15: Average median rate over all hours

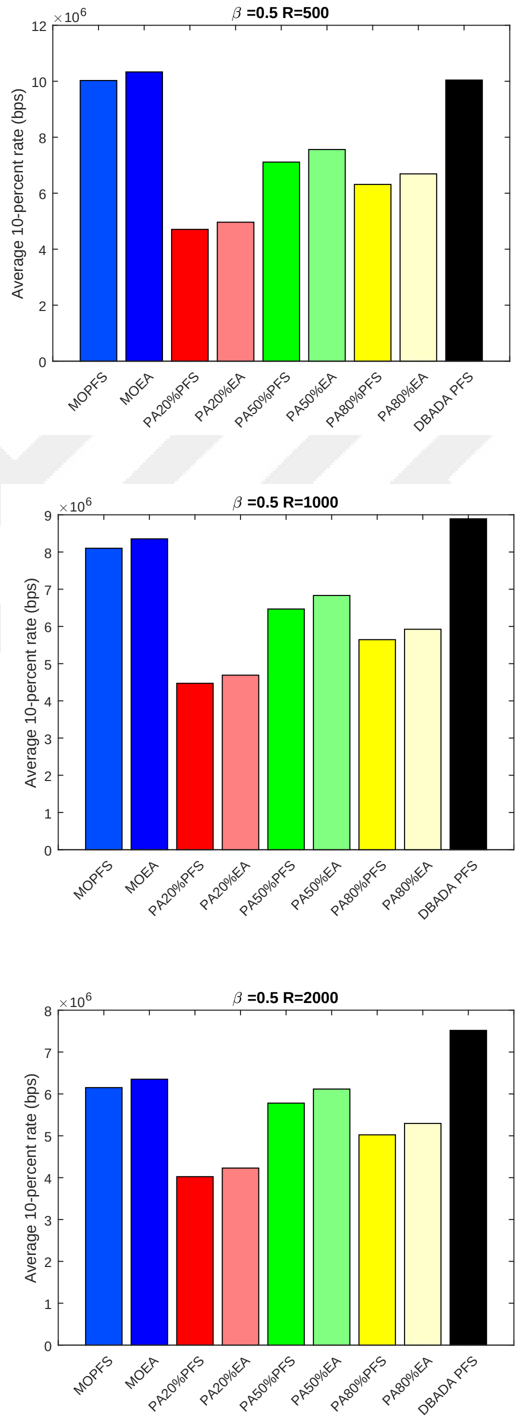


Figure 4.16: Average 10-percent rate over all hours

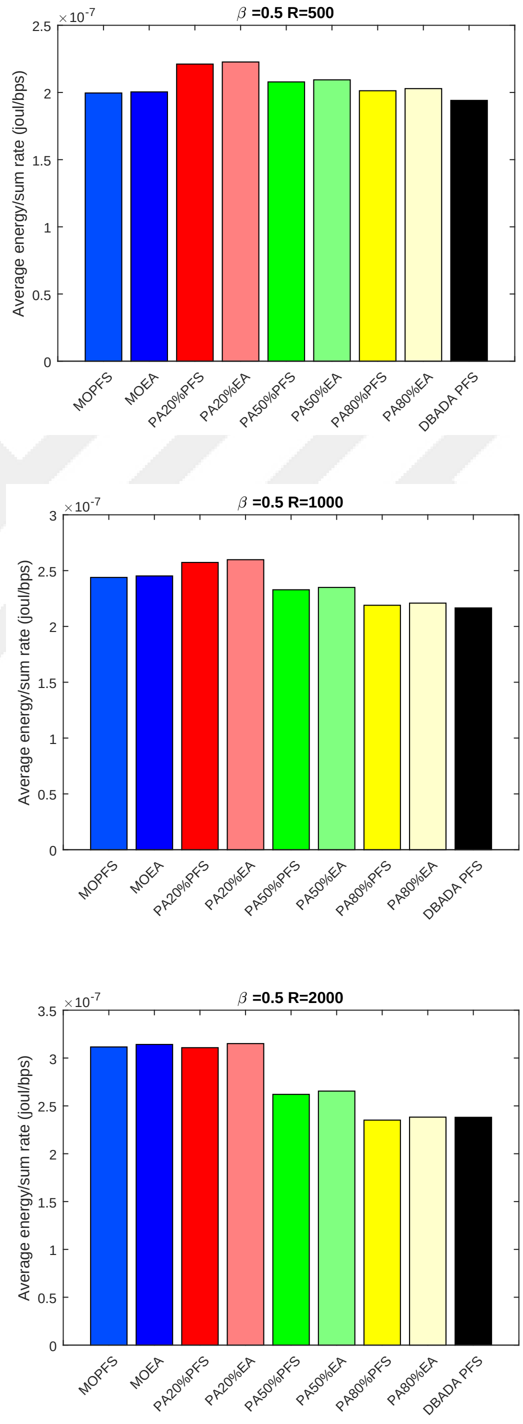


Figure 4.17: Average of energy per sum rate over all hours

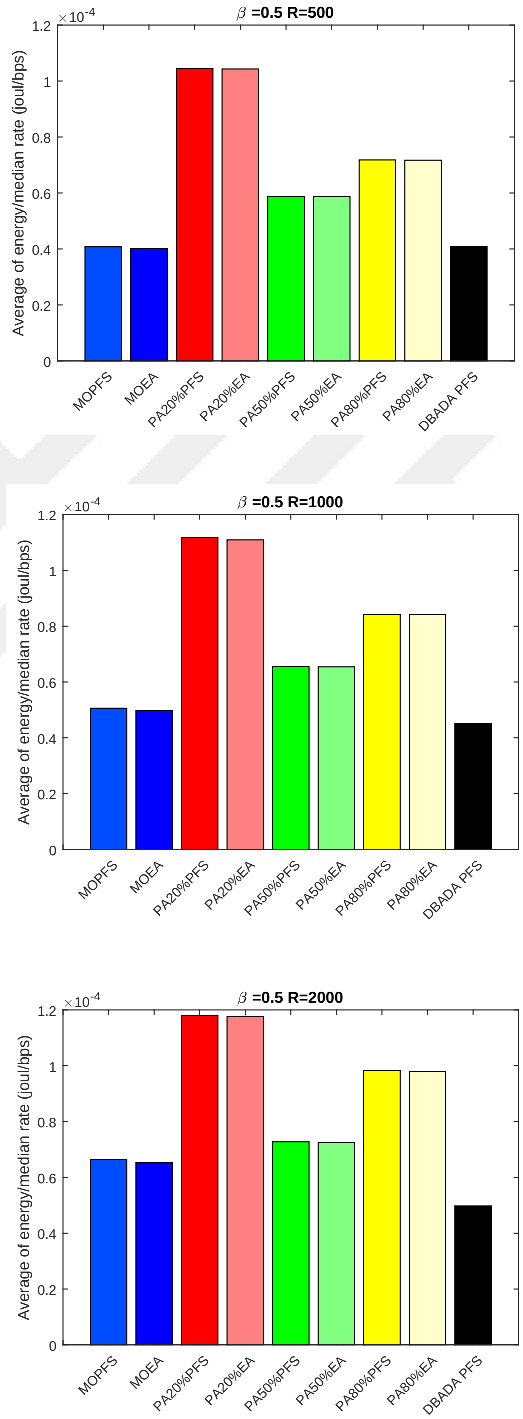


Figure 4.18: Average of energy per median rate over all hours

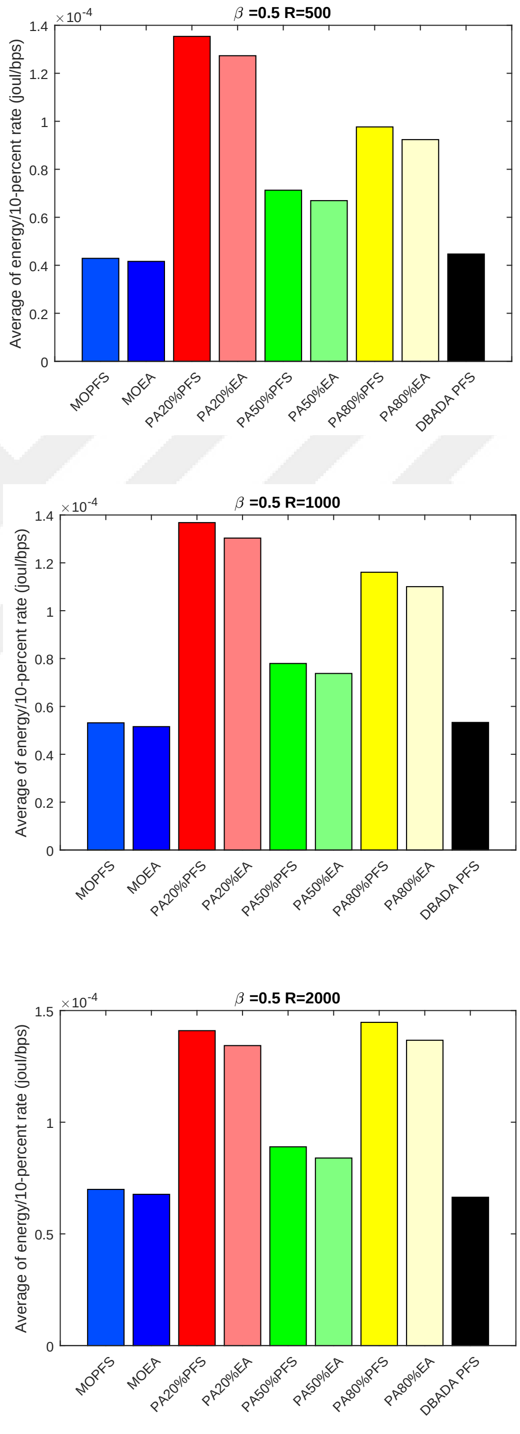


Figure 4.19: Average of energy per 10-percent rate over all hours

In average sum rate plot, Figure 4.14, the best strategy is Picos Active with 80% BW and PFS which, as discussed before, is in line with intuition since the pico cell users mostly enjoy stronger signals than macro cell users. Thus, providing pico cells more resources results in better sum rate performance. However, since Picos Active scenarios are not energy efficient, the best performing scenario in terms of average energy per unit of sum rate is DBADA with PFS, as depicted in Figure 4.17. Accordingly, pushing all pico cells to Active state would increase the cost of network without bringing back enough benefits.

In Figure 4.15, however, DBADA with PFS, which provides global proportional fairness in the network, shows the best performance in terms of average median rate. Not only that but also with consuming less energy, DBADA provides a considerable gain in average energy per unit of median rate, Figure 4.18.

On the other hand, as depicted in Figure 4.16, in average 10-percent rate the best performing strategy is DBADA with PFS. The loose performance of Pico Active scenarios in some hours result in a poor average 10-percent rate performance. However, the Macro only provides more acceptable average 10-percent rate than Picos Active scenarios. As a result, in average energy per unit of 10-percent rate metric, Figure 4.19, DBADA with PFS and Macro only with PFS provide approximately same performance. Consequently, without paying attention to energy efficient deployment and resource allocation, small cell deployments could not improve fairness and energy per unit of fairness in the network.

In the following the average performance of Macro only and Picos Active scenarios under PFS, EA and Sum Rate Maximization (SRM) techniques are tabulated. Moreover, the gain of DABDA with PFS over all other strategies are provided.

	Avg. sum rate	Avg. median rate	Avg. 10% rate
MOPFS	2.158e9	1.004e7	9.558e6
MOSRM	2.494e9	2.906e6	2.162e6
MOEA	2.150e9	1.017e7	9.837e6
PA20%PFS	2.234e9	5.615e6	3.322e6
PA20%SRM	2.589e9	2.042e5	2.623e4
PA20%EA	2.221e9	5.704e6	3.529e6
PA50%PFS	2.386e9	8.712e6	7.032e6
PA50%SRM	2.819e9	2.736e5	3.712e4
PA50%EA	2.369e9	8.666e6	7.467e6
PA80%PFS	2.482e9	9.951e6	7.035e6
PA80%SRM	2.993e9	2.856e5	3.270e4
PA80%EA	2.462e9	1.017e7	7.437e6
DBADA PFS	2.356e9	1.064e7	9.556e6

Table 4.4: The average achievements of simulated strategies, $R = 500m$.

	Avg. sum rate	Avg. median rate	Avg. 10% rate
MOPFS	1.766e9	8.357e6	7.982e6
MOSRM	2.218e9	1.662e6	1.435e6
MOEA	1.756e9	8.492e6	8.221e6
PA20%PFS	1.926e9	5.333e6	3.487e6
PA20%SRM	2.359e9	2.189e5	1.736e4
PA20%EA	1.908e9	5.297e6	3.673e6
PA50%PFS	2.123e9	8.230e6	6.863e6
PA50%SRM	2.572e9	3.174e5	3.126e4
PA50%EA	2.104e9	8.225e6	7.229e6
PA80%PFS	2.264e9	9.543e6	6.221e6
PA80%SRM	2.729e9	3.655e5	3.783e4
PA80%EA	2.245e9	9.861e6	6.552e6
DBADA PFS	2.219e9	1.053e7	8.836e6

Table 4.5: The average achievements of simulated strategies, $R = 1000m$.

	Avg. sum rate	Avg. median rate	Avg. 10% rate
MOPFS	1.392e9	6.239e6	5.910e6
MOSRM	1.805e9	1.234e6	1.129e6
MOEA	1.380e9	6.357e6	6.106e6
PA20%PFS	1.611e9	4.780e6	3.186e6
PA20%SRM	2.030e9	1.657e5	1.521e4
PA20%EA	1.590e9	4.794e6	3.422e6
PA50%PFS	1.892e9	7.185e6	5.760e6
PA50%SRM	2.346e9	2.378e5	2.212e4
PA50%EA	1.867e9	7.191e6	6.130e6
PA80%PFS	2.117e9	8.113e6	5.185e6
PA80%SRM	2.617e9	2.624e5	1.993e4
PA80%EA	2.089e9	8.363e6	5.478e6
DBADA PFS	2.088e9	9.633e6	7.271e6

Table 4.6: The average achievements of simulated strategies, $R = 2000m$.

	Avg. of energy/sum rate	Avg. of energy/median rate	Avg. of energy/10% rate
MOPFS	1.994e-7	4.286e-5	4.507e-5
MOSRM	1.748e-7	1.071e-3	1.989e-4
MOEA	2.001e-7	4.232e-5	4.377e-5
PA20%PFS	2.214e-7	1.240e-4	1.624e-4
PA20%SRM	1.933e-7	5.141e-3	1.353e-1
PA20%EA	2.226e-7	1.240e-4	1.524e-4
PA50%PFS	2.058e-7	5.955e-5	7.277e-5
PA50%SRM	1.749e-7	2.509e-3	5.725e-2
PA50%EA	2.072e-7	5.963e-5	6.838e-5
PA80%PFS	1.974e-7	5.763e-5	7.991e-5
PA80%SRM	1.640e-7	2.205e-3	3.897e-2
PA80%EA	1.990e-7	5.801e-5	7.593e-5
DBADA PFS	1.928e-7	4.276e-5	4.761e-5

Table 4.7: The average achievements of simulated strategies, $R = 500m$.

	Avg. of energy/sum rate	Avg. of energy/median rate	Avg. of energy/10% rate
MOPFS	2.439e-7	5.158e-5	5.440e-5
MOSRM	1.981e-7	2.562e-3	2.997e-4
MOEA	2.453e-7	5.076e-5	5.242e-5
PA20%PFS	2.562e-7	1.212e-4	1.538e-4
PA20%SRM	2.114e-7	3.368e-3	7.317e-2
PA20%EA	4.584e-7	1.219e-4	1.460e-4
PA50%PFS	2.310e-7	6.175e-5	7.305e-5
PA50%SRM	1.912e-7	2.291e-3	3.435e-2
PA50%EA	2.330e-7	6.160e-5	6.936e-5
PA80%PFS	2.166e-7	6.378e-5	9.824e-5
PA80%SRM	1.797e-7	2.683e-3	2.860e-2
PA80%EA	2.185e-7	6.372e-5	9.330e-5
DBADA PFS	2.149e-7	4.561e-5	5.445e-5

Table 4.8: The average achievements of simulated strategies, $R = 1000m$.

	Avg. of energy/sum rate	Avg. of energy/median rate	Avg. of energy/10% rate
MOPFS	3.101e-7	6.916e-5	7.284e-5
MOSRM	2.467e-7	2.774e-3	3.809e-4
MOEA	3.126e-7	5.795e-5	7.055e-5
PA20%PFS	3.060e-7	1.229e-4	1.680e-4
PA20%SRM	2.460e-7	3.689e-3	6.703e-2
PA20%EA	3.100e-7	1.297e-4	1.574e-4
PA50%PFS	2.595e-7	7.126e-5	8.734e-5
PA50%SRM	2.095e-7	2.311e-3	3.332e-2
PA50%EA	2.630e-7	7.109e-5	8.225e-5
PA80%PFS	2.336e-7	8.284e-5	1.275e-4
PA80%SRM	1.880e-7	2.806e-3	3.443e-2
PA80%EA	2.369e-7	8.206e-5	1.203e-4
DBADA PFS	2.342e-7	5.113e-5	6.826e-5

Table 4.9: The average achievements of simulated strategies, $R = 2000m$.

	Avg. sum rate	Avg. median rate	Avg. 10% rate
MOPFS	9%	6%	0%
MOSRM	-5%	266%	343%
MOEA	10%	4%	-3%
PA20%PFS	6%	89%	188%
PA20%SRM	-9%	5200%	31766%
PA20%EA	6%	87%	171%
PA50%PFS	-1%	22%	36%
PA50%SRM	-16%	3433%	23800%
PA50%EA	0%	23%	28%
PA80%PFS	-5%	7%	36%
PA80%SRM	-21%	3433%	31766%
PA80%EA	-4%	5%	28%

Table 4.10: The average improvement of DBADA with PFS strategy over other strategies, $R = 500m$.

	Avg. sum rate	Avg. median rate	Avg. 10% rate
MOPFS	25%	25%	11%
MOSRM	0%	518%	514%
MOEA	27%	24%	8%
PA20%PFS	15%	98%	153%
PA20%SRM	-6%	5150%	44100%
PA20%EA	16%	99%	141%
PA50%PFS	5%	28%	29%
PA50%SRM	-14%	3400%	29366%
PA50%EA	5%	28%	22%
PA80%PFS	-2%	11%	42%
PA80%SRM	-19%	2525%	22000%
PA80%EA	-1%	7%	35%

Table 4.11: The average improvement of DBADA with PFS strategy over other strategies, $R = 1000m$.

	Avg. sum rate	Avg. median rate	Avg. 10% rate
MOPFS	50%	54%	23%
MOSRM	15%	683%	543%
MOEA	51%	51%	19%
PA20%PFS	30%	101%	128%
PA20%SRM	3%	5919%	36250%
PA20%EA	31%	101%	112%
PA50%PFS	11%	34%	26%
PA50%SRM	-11%	3913%	36250%
PA50%EA	12%	34%	18%
PA80%PFS	-1%	19%	40%
PA80%SRM	-20%	3604%	36250%
PA80%EA	0%	15%	33%

Table 4.12: The average improvement of DBADA with PFS strategy over other strategies, $R = 2000m$.

	Avg. of energy/sum rate	Avg. of energy/median rate	Avg. of energy/10% rate
MOPFS	3%	0%	-6%
MOSRM	-10%	99%	76%
MOEA	4%	-1%	-9%
PA20%PFS	14%	65%	72%
PA20%SRM	0%	99%	99%
PA20%EA	13%	65%	69%
PA50%PFS	4%	28%	36%
PA50%SRM	-10%	99%	99%
PA50%EA	7%	28%	30%
PA80%PFS	2%	27%	42%
PA80%SRM	-18%	99%	99%
PA80%EA	3%	26%	38%

Table 4.13: The average improvement of DBADA with PFS strategy over other strategies, $R = 500m$.

	Avg. of energy/sum rate	Avg. of energy/median rate	Avg. of energy/10% rate
MOPFS	12%	12%	0%
MOSRM	-9%	98%	82%
MOEA	13%	10%	-4%
PA20%PFS	16%	63%	65%
PA20%SRM	-2%	99%	99%
PA20%EA	53%	62%	63%
PA50%PFS	7%	27%	26%
PA50%SRM	-12%	99%	99%
PA50%EA	8%	26%	21%
PA80%PFS	1%	29%	45%
PA80%SRM	-19%	99%	99%
PA80%EA	2%	28%	42%

Table 4.14: The average improvement of DBADA with PFS strategy over other strategies, $R = 1000m$.

	Avg. of energy/sum rate	Avg. of energy/median rate	Avg. of energy/10% rate
MOPFS	25%	26%	6%
MOSRM	5%	98%	82%
MOEA	25%	12%	3%
PA20%PFS	24%	59%	60%
PA20%SRM	5%	99%	99%
PA20%EA	25%	60%	56%
PA50%PFS	10%	29%	22%
PA50%SRM	-11%	98%	98%
PA50%EA	11%	28%	17%
PA80%PFS	0%	39%	47%
PA80%SRM	-24%	98%	98%
PA80%EA	1%	14%	43%

Table 4.15: The average improvement of DBADA with PFS strategy over other strategies, $R = 2000m$.

Generally, the SRM technique would result in a very poor fairness which makes it an uninteresting technique in our simulation platform. Thus, the following comparisons include PFA and EA techniques.

In $R = 500m$, except MOEA which also performs very close, DBADA with PFS performs better than all strategies in average sum rate, median rate and 10-percent rate metrics, Tables 4.4 and 4.7. In 10-percent rate, Table 4.4, the improvement of DBADA with PFS strategy compared to Picos Active scenarios scales somewhere between 28% and 188%. Likewise, in median rate, DBADA with PFS achieves up to 89% improvement over Macro only scenarios. However, compared to Macro only with PFS and EA the median rate and 10-percent rate improvements are limited to a few percentages. In energy per unit of median rate and 10-percent rate, Table 4.7, Macro only outperforms DBADA with PFS. The main reason is the smaller improvement capacity of COE deployment in small macro cells. Nevertheless, DBADA with PFS still achieves up to 65% and 72% improvement in average energy per unit of median rate and average energy per unit of 10-percent rate, respectively, Table 4.7.

In $R = 1000m$, DBADA with PFS achieves highest median and 10-percent rates among all other strategies, Table 4.5. The improvements are up to 153% in 10-percent rate and 99% in median rate compared to Picos Active scenarios. Moreover, it improves median rate and 10-percent rate by at least 24% and 8% compared to Macro only scenarios. On the other hand, up to 65% improvement is achieved by DBADA with PFS in the energy per unit of median rate and the energy per unit of 10-percent rate, Table 4.8.

Finally, in $R = 2000m$, DBADA achieves up to 101% and 128% improvements in average median rate and average 10-percent rate, respectively, Table 4.6. Moreover, as it is stated in Table 4.7, it improves both average energy per unit of median rate and average energy per unit of 10-percent rate up to 60%. On the other hand, in $R = 2000m$, the improvement of DBADA with PFS over

Macro only scenario is more dominant, since the larger the macro cell the worse the cell edge experience will be. Therefore, by placing small cells at the cell edge of larger macro cell the higher fairness improvements are expected.

4.3.1 Rate-Energy Trade-Off

In the following we will study the performance of system for different values of β, where $R = 1000$m.

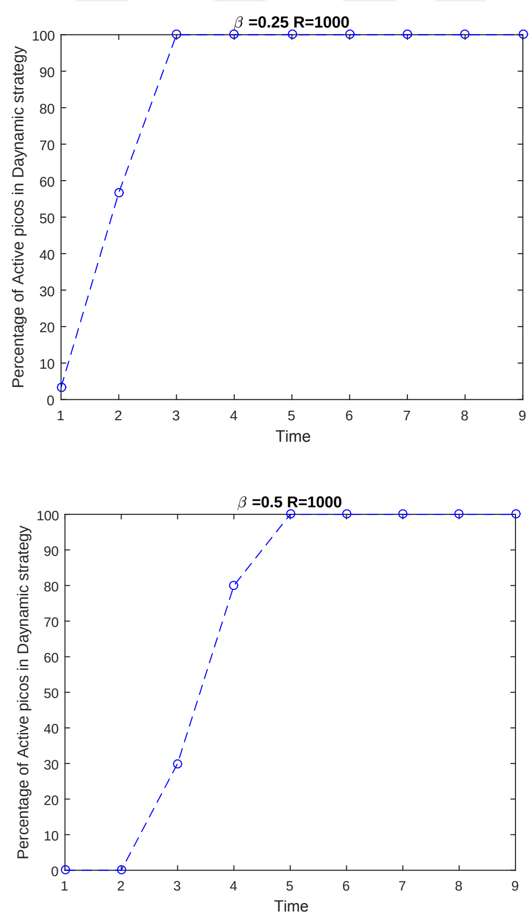


Figure 4.20: Average number of Active picos

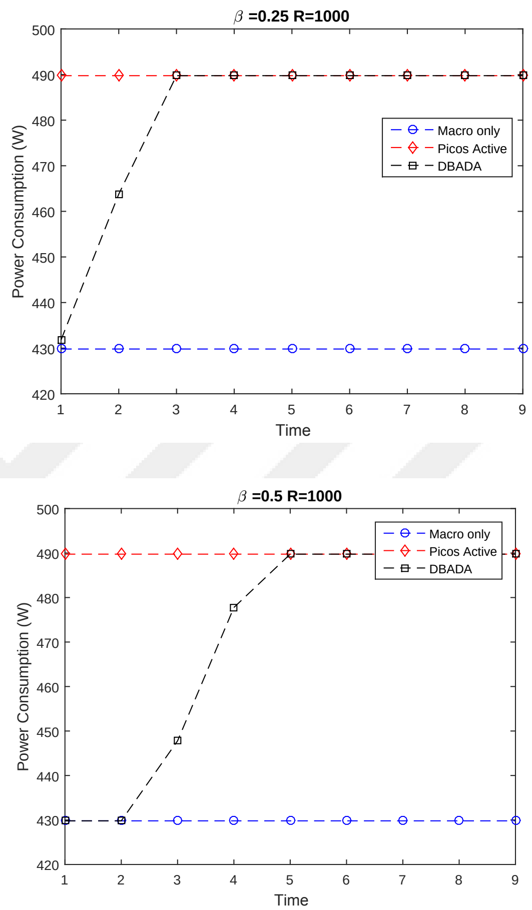


Figure 4.21: Power consumption

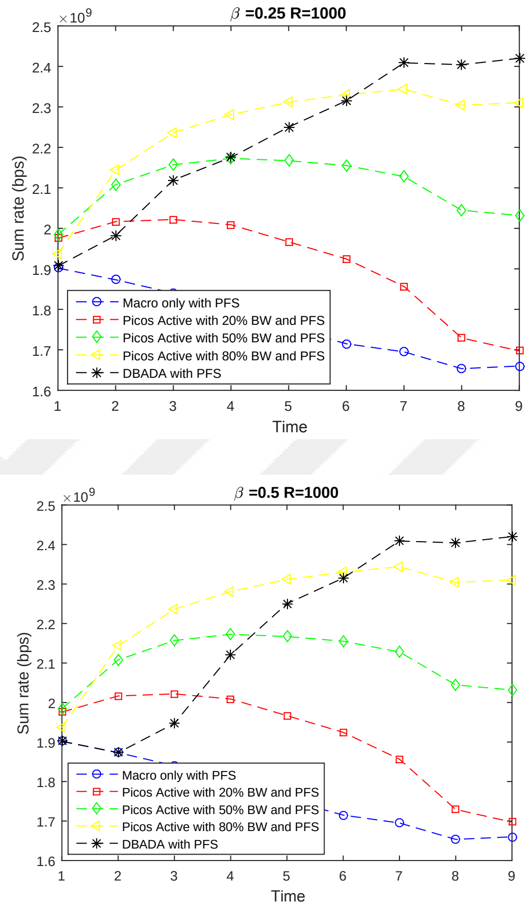


Figure 4.22: Sum rate

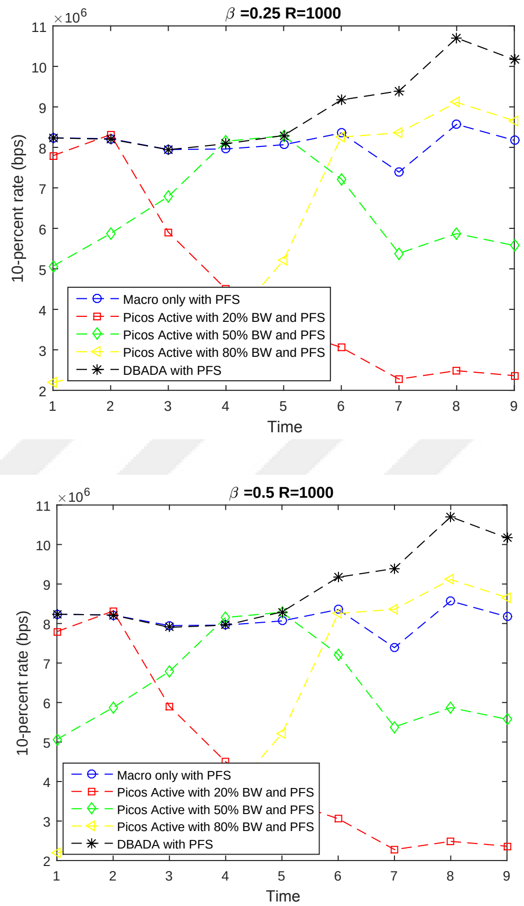


Figure 4.23: 10-percent rate

By increasing β, which captures the relative price of energy in the environment, it is observed that DBADA with PFS strategy decreases the number of Active picos, Figure 4.20. It is basically because by turning each pico to Active state we are increasing the power consumption of the system. Therefore, the DBADA strategy pushes more picos to idle state in the higher-priced energy environments to save more power, Figure 4.21.

As it is depicted in Figure 4.22, reducing β from 0.5 to 0.25 does not affect the sum rate performance in peak or off-peak hours. However, the greater sum rate in median hours for $\beta = 0.25$ shows that the DBADA with PFS could achieve greater sum rates in lower-priced energy environments. Nevertheless, as it is shown in Figure 4.23, 10-percent rate has a negligible growth, again only in median hours, when β decreases, since the tail of rate distribution is less sensitive to any change than sum rate.

4.3.2 Penalized Users Distribution

The locations of penalized users, which are the users who achieve less than 10% rate in the network, in Macro only, Picos Active and DBADA strategies for hour 3, 4 and 5 are depicted in following figures. The number of Active picos in DBADA strategy at hour 3, 4 and 5 are 1, 2 and 3, respectively.

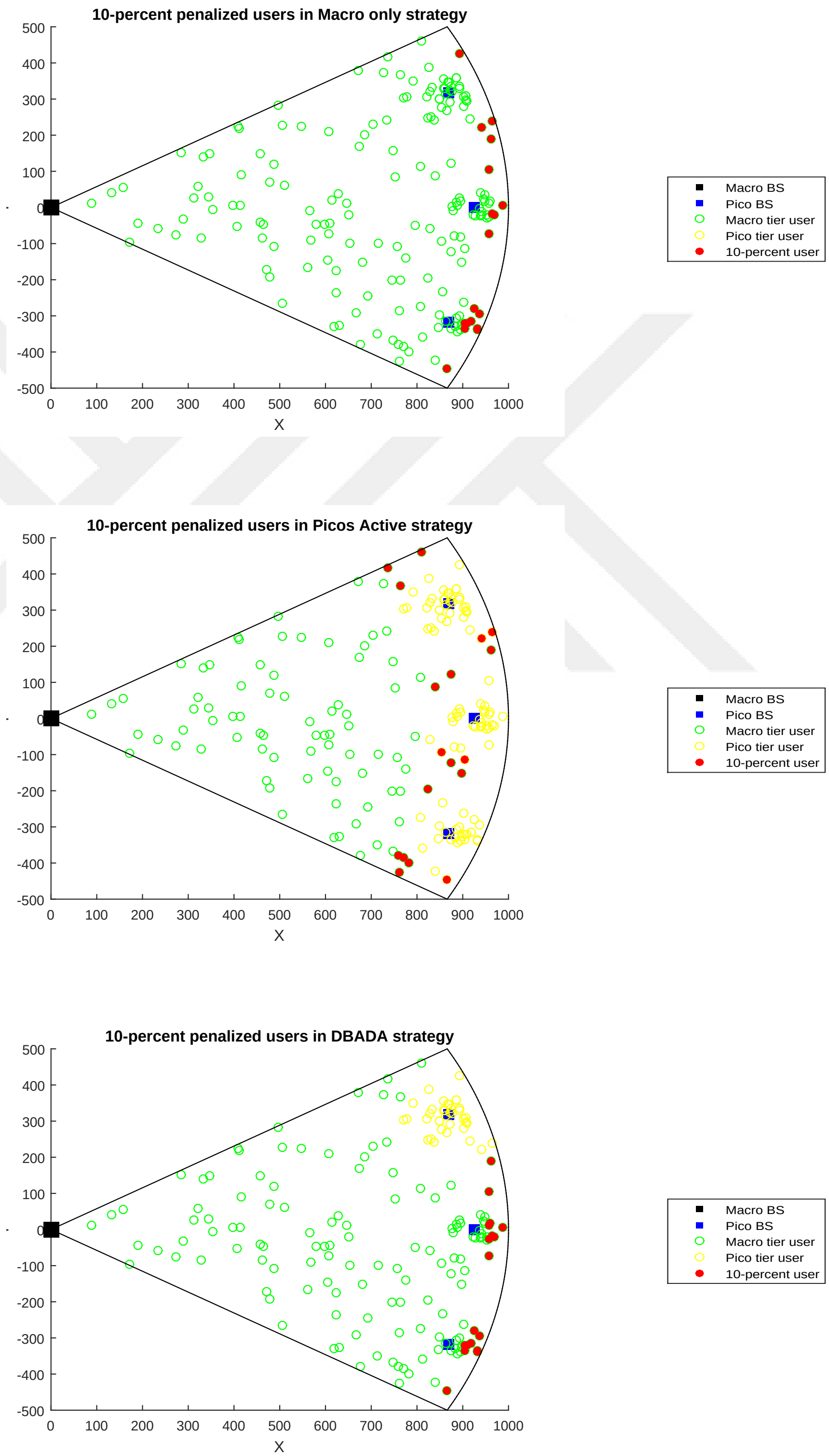


Figure 4.24: 10-percent penalized users

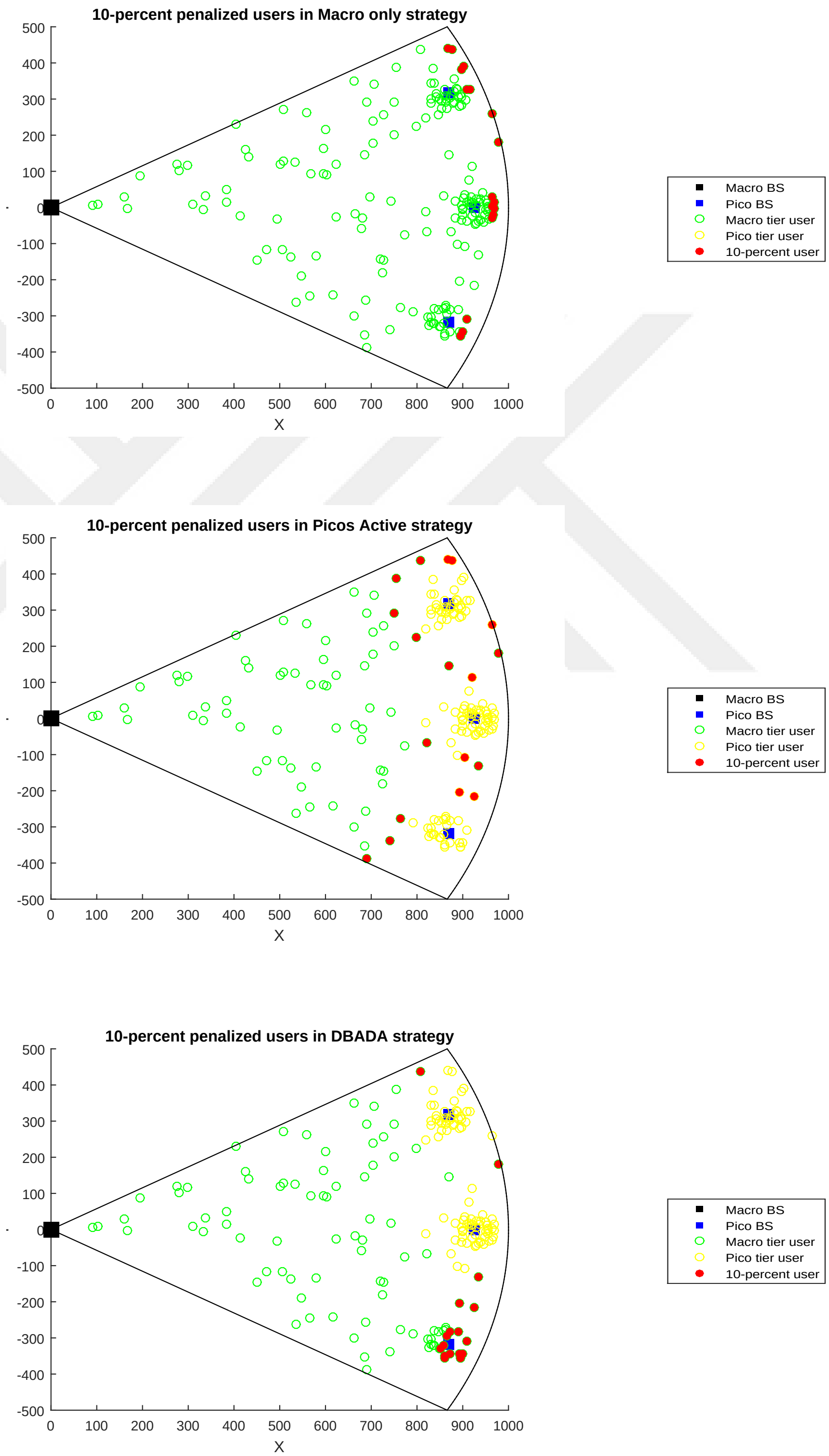


Figure 4.25: 10-percent penalized users

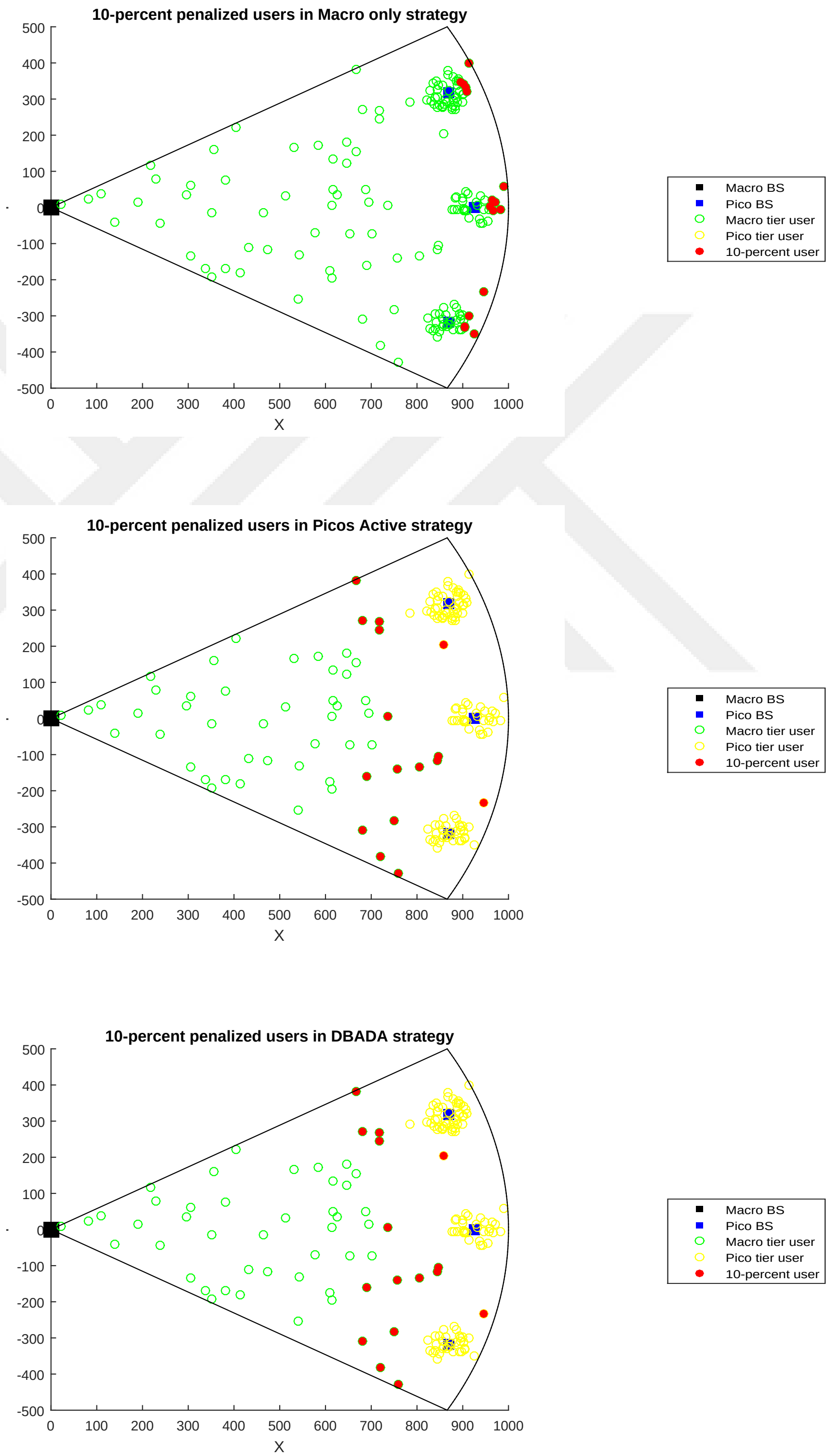


Figure 4.26: 10-percent penalized users

Chapter 5

Conclusion

A dynamic resource allocation and dynamic activation strategy for improving energy efficiency and fairness in HetNet is proposed, where the traffic intensity at each cell changes over time. The strategy is implemented in an HetNet where, to improve the penalized users' experience, small cells are located at the edge of the macro cell. The optimization problem of joint energy efficient and utility optimum HetNet is formulated and the existence of global optimum is proved. Under high SNR analysis, the behaviour of the solution is discussed. The performance of the proposed strategy is evaluated with respect to Macro only scenario and Picos Active scenarios with different static resource allocation schemes. The rate of 10-percent user and median user, as fairness metrics, along with the network sum rate performance are studied. Moreover, the price of the aforementioned metrics, in terms of energy per bit, are evaluated. By introducing a new constant to the optimization problem, we also take the price of the energy in the studied environment into account.

In the dynamic traffic scenario, through our simulations we illustrate that a static resource allocation results in a poor overall performance in small cell networks. More specifically, assigning each small cell a specific amount of resources in all of the traffic intensities deteriorates the fairness performance. For instance, while 20% of resources at small cells guarantees an acceptable level of fairness in off-peak hours, it fails to adapt to the more intense traffic at peak hours. Further, assigning small cells 50% and 80% of resources only guarantee an acceptable fairness in the median hours and peak hours, respectively, and fails in other traffic intensities. Moreover, when considering energy consumption as another decision factor, it is observed that Macro only scenario could achieve a comparable performance compared to Picos Active scenarios and, therefore, placing small cells into Idle state would save more energy with a negligible penalty. However, in median to peak hours of traffic a huge gap between macro only and Picos Active scenarios is observed.

Nevertheless, DBADA strategy takes both dynamic activation and dynamic resource allocation into account. From our numerical results it can be observed that the best strategy, in terms of 10-percent rate and median rate, is DBADA and, at the same time, it has a close-to-maximum sum rate performance. Furthermore, due to the energy awareness of DBADA strategy, it outperforms other strategies in energy over rate metrics. Compared to Picos Active scenarios, DBADA decreases the energy consumption per unit of median and 10-percent rates by at least 26% and 21%, respectively, in medium size cells. These improvements are even greater in larger cells.

According to our results, placing small cells to Active state and allocating them same amount of resources for all traffic variations in HetNets could affects negatively on network energy consumption and decreases fairness in the network dramatically. Therefore, for future studies on fairness in HetNets, dynamic resource allocation should be considered. Moreover, proposing a distributed algorithm for such a dynamic allocation would reduce the centralized computational burden. In addition, reducing the Active/Idle switching problem size could be an interesting topic for future studies.

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