# E-ASSOC: ENHANCED ENERGY EFFICIENT USER ASSOCIATION ALGORITHM FOR FUTURE CELLULAR NETWORKS

by

**MAREESH KUMAR ISSAR**

**A thesis submitted to the**

**School of Graduate Studies**

**Rutgers, The State University of New Jersey**

**In partial fulfillment of the requirements**

**For the degree of**

**Master of Science**

**Graduate Program in Electrical and Computer Engineering**

**Written under the direction of**

**Dipankar Raychaudhuri**

**And approved by**

**New Brunswick, New Jersey**

**October, 2020**

## ABSTRACT OF THE THESIS

# E-ASSOC: Enhanced Energy Efficient User ASSOCiation Algorithm for Future Cellular Networks

**By MAREESH KUMAR ISSAR**

**Thesis Director:**
**Dipankar Raychaudhuri**

Future cellular networks need to reduce their carbon footprint in view of rapidly increasing data traffic from emerging applications including Augmented Reality (AR)/ Virtual Reality (VR), autonomous vehicles and Internet of Things (IoT). A potential solution is the addition of small base stations, overlaid upon the macro base station, installed at locations encountering traffic hotspot or a coverage gap. However, the addition of base stations leads to an increase in the overall static network power consumption. Algorithms for energy efficiency aim to strike a balance between network throughput and power consumption. In this work, we evaluate several existing optimization based user association algorithms focusing on load balancing and power minimization metrics. Verification of the performance for all user association algorithms is carried out using MATLAB based system level simulator for a network topology comprising of one macro and four pico base stations considering static users. Motivated by the gains demonstrated using optimization based schemes, we consider the design of a lower complexity class of heuristic user association algorithms with comparable performance. The proposed E-ASSOC algorithm utilizes load at each base station and the difference amongst the two best Signal to Noise Ratios (SNRs) for each user as its threshold metrics. Simulation results demonstrate a gain of 41.26% in the total system throughput along with reduction of 32.96% in the system power consumption. Eventually indicating an increase of 87.83% in energy efficiency over the baseline max-SNR based association algorithm along with decrease of 7.2% for load balancing algorithm and 10.13% for power minimization algorithm. Fairness of the algorithms examined using Jain's Fairness Index (JFI) also shows marked improvement over the baseline scheme.

## Acknowledgements

First and foremost, I would like to thank my advisor Professor Dipankar Raychaudhuri for his patience and constant guidance. He is the best advisor I could have asked for. Despite his busy schedule, he always had time to answer my professional and personal queries by providing nuggets of information whenever I got stuck. He has always been a constant source of motivation and his advice on focusing on fundamentals, trying to be original and innovative in your work, setting ambitious technology goals for your work and thinking about the broader impact on society has struck a chord with me.

I would also like to thank my committee members Professor Roy Yates and Professor Predrag Spasojevic for their valuable feedback, insights, and approach on formulating and deciphering research problems throughout the duration of this project.

I would also like to express my heartfelt gratitude to all the WINLAB faculty and staff members especially Ivan Seskar for always squeezing in time from his busy schedule to respond to my questions.

I am extremely grateful to all my WINLAB labmates - Prasad Netalkar for endless car journeys, constant mentoring and motivation. Siddharth Rupavatharam for always being available for discussions on almost any topic. Mohsen Rajabpour, Vishakha Ramani, Dr. Sumit Maheshwari, Dr. Jiachen Chen, Wuyang Zhang, Mohammad Yousefvand, and Shalini Choudhury for debugging my work.

Finally, I would like to express my sincere gratitude to my family members especially my mother and my father for their constant encouragement, support, and unconditional love. Thank you for everything!

# Dedication

*To my mother Dr. Pratibha Issar, my father Dr. Sanjeev Kumar Issar and my younger brother Arnesh Kumar Issar*

# Table of Contents

**Abstract** . . . . . . . . . . ii

**Acknowledgements** . . . . . . . . . . iv

**Dedication** . . . . . . . . . . v

**List of Tables** . . . . . . . . . . viii

**List of Figures** . . . . . . . . . . ix

**1. Introduction** . . . . . . . . . . 1

1.1. Problem Statement . . . . . . . . . . 4

1.2. Main Contributions . . . . . . . . . . 6

**2. Cellular System Background** . . . . . . . . . . 7

2.1. Homogeneous Networks . . . . . . . . . . 7

2.2. Heterogeneous Networks . . . . . . . . . . 7

2.3. User Association . . . . . . . . . . 9

2.4. Energy Efficiency . . . . . . . . . . 11

**3. System Model** . . . . . . . . . . 13

3.1. System Assumptions . . . . . . . . . . 13

3.2. System Model . . . . . . . . . . 14

3.3. Performance Evaluation Metrics . . . . . . . . . . 16

3.3.1. Fairness . . . . . . . . . . 16

3.3.2. System Throughput . . . . . . . . . . 17

3.3.3. System Power Consumption . . . . . . . . . . 18

**4. User Association Algorithms** . . . . . . . . . . . . . . . . . . . . . . . . . . . 21

4.1. Max-SNR based User Association Algorithm . . . . . . . . . . . . . . . . 21

4.2. Load Balancing based User Association Algorithm . . . . . . . . . . . . 22

4.3. Power Minimization based User Association Algorithm . . . . . . . . . . 24

4.4. E-ASSOC User Association Algorithm . . . . . . . . . . . . . . . . . . . 26

**5. Evaluation Results** . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 29

**6. Conclusion and Future Work** . . . . . . . . . . . . . . . . . . . . . . . . . . 33

6.1. Conclusion . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 33

6.2. Future Work . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 33

**Bibliography** . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 34

# List of Tables

1.1. Taxonomy metrics for user association algorithm . . . . . . . . . . . . . 5

2.1. Types of channel allocation schemes . . . . . . . . . . . . . . . . . . . . . 10

3.1. Simulation parameters. Legend: BS = Base Station, RB = Resource Blocks . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 16

3.2. Notations used in equation 3.2 . . . . . . . . . . . . . . . . . . . . . . . . 19

3.3. Power consumption model parameter values for base stations . . . . . . 19

3.4. Energy consumption range for base stations . . . . . . . . . . . . . . . . 20

4.1. Notations used throughout the thesis . . . . . . . . . . . . . . . . . . . . 23

4.2. Power consumption model parameter values for base stations . . . . . . 25

5.1. Max-SNR Vs Load balancing Vs Power minimization user association algorithms . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 29

5.2. Max-SNR Vs E-ASSOC user association algorithm . . . . . . . . . . . . 30

5.3. Mean user throughput and JFI analysis for Max-SNR Vs Load balancing Vs Power minimization user association algorithms . . . . . . . . . . . . 31

5.4. Mean user throughput and JFI analysis for Max-SNR vs E-ASSOC user association algorithms . . . . . . . . . . . . . . . . . . . . . . . . . . . 32

# List of Figures


1.1. System Model . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 5

3.1. Simulation network topology . . . . . . . . . . . . . . . . . . . . . . . . . 14

3.2. Power consumption Vs relative RF output power for macro and pico base station (based on values from table 3.3) . . . . . . . . . . . . . . . . . . . 18

4.1. Summary of approaches used for solving optimization equation . . . . . 27

5.1. Load at each base station after execution of user association algorithms 30

5.2. Comparison of average user throughput for all user association algorithms considering 200 simulation runs (60 users per run) . . . . . . . . 31

# Chapter 1

# Introduction

The long-term trend of ever-increasing data demand often follows Cooper's law, where the traffic doubles every two-and-a-half year. According to Ericsson's Mobility Report [1], by 2025 5G networks will carry about 45% of the world's mobile data traffic and have around 2.6 billion subscriptions covering up to 65% of world's population. A wide range of upcoming applications like autonomous vehicles, Internet of Things (IoT), and edge computing all contribute to a substantial data rate and bandwidth requirement.

Fulfillment of the increasing data demands for current as well as emerging cellular networks is often associated with a surge in network-wide energy consumption. The 2015 report [2] estimates that 1.15% (242 TWh) of the total electricity grid supply globally was consumed by telecom networks which also resulted in 0.53% (169 Mt) of the global carbon emissions (energy related). Air conditioning and signal processing circuits consume about 60% of power dissipated at the base stations [3]. Putting the base stations with no load into sleep mode helps in saving power consumed by the network [4]. To reduce power consumption at the base station, 5G New Radio (NR) takes advantage of base station sleep mode and traffic activity pattern. Other solutions include the use of energy-saving software and operating site infrastructure proactively using Artificial Intelligence (AI) [5, 6].

To improve the cellular energy efficiency, without sacrificing Quality-of-Service (QoS) at the users, the network topology could be densified to enable higher spatial reuse. This is achieved by overlaying a layer of Small Cell Access points (SCAs) to offload traffic from macro cells, exploiting the fact that most data traffic is localized. Recent deployment of city-scale programmable testbeds like COSMOS [7] have enabled researchers to deploy and test their applications and algorithms (pertaining to future wireless networks) on such emerging topics in a real-world environment.

The upcoming 5G cellular network is expected to support the following requirements:

- Increased demand for data.
- Improved QoS.
- Reduced Energy Consumption.

Key technologies proposed to accomplish these objectives are heterogeneous network [8], mmWave [9], massive MIMO (Multiple Input and Multiple Output) [10], and Centralized Radio Access Network (C-RAN). Heterogeneous network (HetNet) consists of low complexity small cells like picocell, femtocell and relay, deployed inside the macrocell coverage region, transmitting at power lower than the macro. These small cells help to offload traffic and improve the spectral efficiency. Owing to their small size, they are generally easier to install, run and maintain.

User association refers to the process which determines the base station to which a user will associate before the data transmission begins. Liu *et al.* in [11] have extensively analyzed existing user association algorithms and their impact on various upcoming technologies for 5G. Traditional user association algorithms tend to attach users to the base station from which they receive the strongest signal [12]. This approach works adequately for a homogeneous network with a small number of users. But such a scheme overlooks the possibility of load balancing across lightly loaded neighbouring base stations. The problem is further intensified in a heterogeneous scenario [13]. The user association problem morphs itself into the re-association and handover problem when the users in the system are mobile [14].

In a HetNet scenario, maximum signal strength based association scheme leads to underutilization of the small cells as most of the users tend to attach to the macro cell (due to its large transmit power). I. Guvenc [15] proposes the use of biased user association as a solution to the problem. This technique changes the power received from the pico base station by adding a fixed bias [16]. Okino *et al.* [17] showed the importance of an adaptive bias factor for different load scenarios. A major drawback of this scheme is that users attached to the small cell (using the bias approach) tend to experience interference from neighbouring macrocell [18]. The issue of interference can be alleviated using 3GPP enhanced intercell interference coordination (eICIC) via almost blank subframes (ABSs) [19].

3GPP Release 8/9 Long-Term Evolution (LTE) HetNet [20] analyzed two schemes, first with open access picocells and the second with closed access femtocell. They showed that a single picocell can double the area spectral efficiency without impacting the macro tier whereas femtocell leads to deterioration of performance in both macro and femto users. Their simulation results was based on actual behaviour of Physical Downlink Shared Channel (PDSCH) rather than Shannon capacity formula.

In cellular networks we often deal with improving metrics like energy efficiency, system throughput, reducing latency etc. Often these metrics are inter-related to one another i.e. if one improves then the other might deteriorate. Reference [21] describes the frameworks for handling the trade offs amongst such conflicting metrics. As the demand for data rises so does the energy consumption of the network. Recently, green communication techniques have been proposed in order to tackle the issue of the increased power consumption [22]. The term energy efficiency (bits/Joule) can be defined as the ratio of the total system level throughput to the system level power consumption [23].

In order to maximize the linear sum of user throughput, the base stations should serve the users who get the best signal because other users with poor signal quantity tend to consume more network resources [24]. Thus another important metric while designing user association algorithm is fairness. Jain's fairness index is a widely used metric for fairness evaluation [25]. Reference [24] examined the problem of network-wide proportional fairness (balancing system throughput while maintaining fairness) by focusing on a generalized objective function.

Cellular system optimizations are generally modelled as utility maximization problem with corresponding resource constraints such as QoS constraints, load constraints at base stations etc. The assumption that a user can be associated to only one base station tends to make the problem combinatorial in nature, which is often NP-Hard. A widely used method to tackle this issue is by treating the user association variable for each user to be a real value in the interval [0,1] rather than a binary variable [26].

3GPP release 12 focuses on dual connectivity techniques [27] for improving the performance related to a mobile user. In dual connectivity, a user receives constant signalling messages from a macro base station. Simulation and investigation of the impact of several user association schemes in the presence of dual connectivity has been presented in [28].

The impact of user mobility in HetNets has been studied in [29] and the results showed an improvement in the overall network performance using a speed-dependent bias factor. Authors in [30] proposed a distributed user association algorithm based on an online reinforcement learning based approach for implementing load balancing in vehicular networks using spatial-temporal traffic pattern.

Recent work like [31] focus on ultra reliable and low latency communication (URLLC) in HetNet solving jointly the issue of user offloading and resource optimization. Base station sleeping strategy based on traffic estimated at the base station using machine learning techniques has been analyzed in [32].

## 1.1 Problem Statement

User association algorithms have been widely studied [11] for their pivotal role in improving the spectrum efficiency, load balancing and energy efficiency of networks. Energy efficiency is defined as the ratio of total network throughput to total network power consumption. Several works have proposed and analyzed optimization based approaches for increasing the network throughput (while maintaining fairness) [26] and reducing the network level power consumption (while maintaining QoS) [33]. A major drawback of such approaches is the computational complexity and large time duration spent on computing the near-optimal values. Thus, the goal of this work is to improve the energy efficiency for cellular networks by designing a low-complexity heuristic based

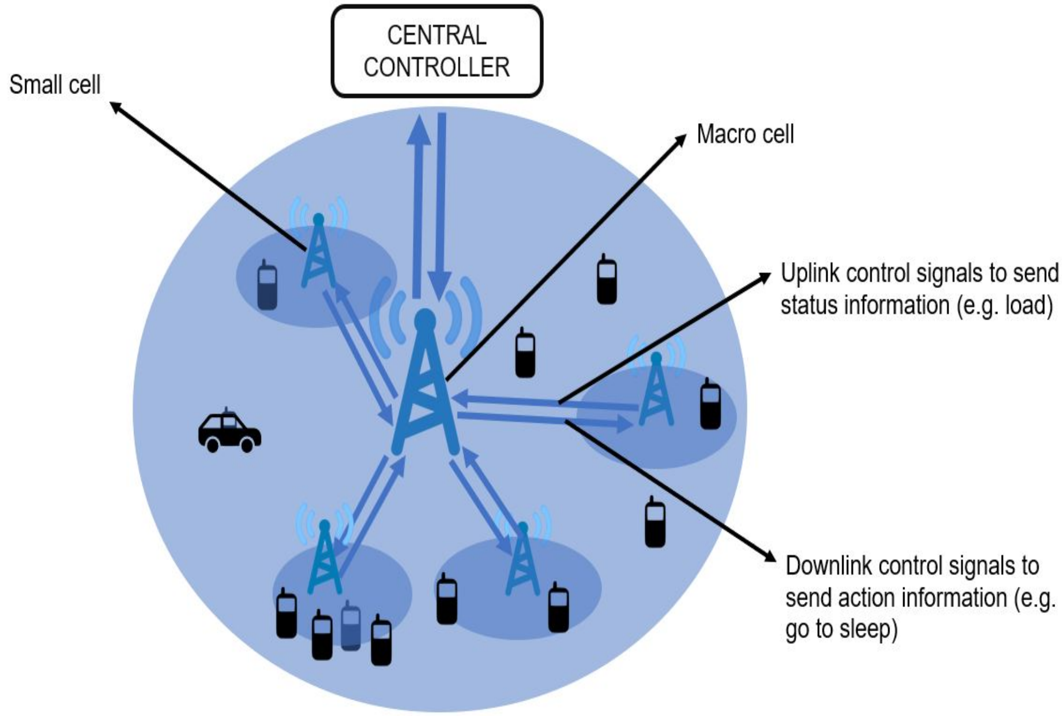


Figure 1.1: System Model

| Categories | Value |
|---|---|
| Scope | HetNets |
| Model | Combinatorial optimization |
| Control | Centralized |
| Metric | Energy efficiency |

Table 1.1: Taxonomy metrics for user association algorithm

algorithm incorporating the intuition behind existing optimization based approaches. Figure 1.1 describes the overall system model used throughout this work.

Using the framework for existing user association algorithms provided in [11], our approach can be categorized in table 1.1 as follows:

The main aim of this work is to provide a centralized low-complexity heuristic based association algorithm. Table 3.1 highlights the specific categories along with their corresponding values (based on taxonomy structure introduced in Fig. 3. in [11]) for the user association algorithm presented in this thesis.

## 1.2 Main Contributions

The major contributions of this work are as follows:

- Comparison of the performance of several existing optimization based user association algorithms with the baseline max-SNR based association algorithm.

- Design and implementation of a low-complexity centralized heuristic based association scheme to improve the system level energy efficiency.

  This work aims to evaluate the performance of optimization based association algorithms for comparison with the max-SNR based association algorithm. We present a heuristic based association algorithm derived from the insights obtained from the optimization based schemes. Detailed MATLAB simulations were carried out to study the performance of all the user association algorithms and their impact on the system level performance using metrics like system level energy efficiency, throughput, power consumption, load at each base station, mean user throughput and JFI.

# Chapter 2

# Cellular System Background

## 2.1 Homogeneous Networks

Homogeneous network refers to a cellular network comprising of base stations having similar capabilities. Cell planning tools often use the concept of frequency reuse for their effective deployment. The base stations are usually deployed on a standalone tower or a building rooftop. They usually have a three sector coverage region, with each sector covering 120°. In order to meet the rising data traffic demands, cellular networks utilize several enhancements over homogeneous networks. In this thesis, we focus our attention on one such enhancement - HetNet.

## 2.2 Heterogeneous Networks

Traditional networks comprised of macro base stations using a single access technology. HetNet on the other hand uses a tiered approach where low-power, low-complexity small base stations are overlaid inside the macro base station's coverage area. Small base stations help in addressing the issue of traffic hot spots and coverage gaps while improving the spectral efficiency and facilitating network infrastructure scaling. Operators usually tend to deploy small base stations in hot spot locations like schools, stadiums or malls. The operator is also responsible for providing the necessary backhaul for them.

The different tiers of base station deployment are distinguished primarily based on their transmit powers [34]. The transmit power for macro base station typically lies in the range of 5W - 40W. Small cells can be classified into the following types:

- Low power outdoor nodes (250mW – 2W).

  - Pico base station: These are typically operator owned. They have a smaller coverage area and lower load capacity as compared to macro base stations.
  - Relay node: They are used to enhance the network coverage [35].

- Femto base station: These are suitable for environments where there is a small variation in the user density, for example in indoor office (with home Digital Subscriber Line (DSL) or cable modem as their backhaul) and have transmit power in the range ($\leq$100mW). They can be configured with the following types of restricted access schemes:
  - Open access: In this access scheme any user can connect to the femto base station.
  - Closed access: In this access scheme only registered users can connect to the femto base station.
  - Hybrid access: In this access scheme any user can connect to the femto base station but registered users will have a higher priority.

In co-channel HetNet deployments (macro and small base stations transmitting at the same frequency) interference coordination techniques are required. Interference might also arise from the femto base stations which allow only registered users to connect to them. Thus macro/small base stations need resource partitioning across them to mitigate these effects. The resource partitioning is done primarily in the time domain (best suited in case of limited spectrum), frequency domain (used primarily for asynchronous networks) or the spatial domain (present in case of Coordinated Multi Point). For the time domain resource partitioning macro base stations transmits certain ABS, during which pico base stations transmit. These are primarily decided based on either the load at the pico base station or the data rate requirement of the users. An important point to note here is that the macro base station transmits the common control signals even during ABS. Other slow adaptive interference mitigation techniques work at a timescale much larger than the scheduling intervals by regulating the transmit power of the base stations for maximizing the total network utility while satisfying the Quality of Service (QoS) constraints of the users.

## 2.3 User Association

The process by which a user attaches/connects to a cell tower (macro base station or small base station) before it starts receiving data is called user association.

Conventional user association mechanisms usually focus on signal strength as their deciding parameter i.e. the user will attach itself to the base station from which it receives the strongest signal [36]. A major drawback of this approach is that since the macro base station transmits at a power that is much higher than the small base station, we can usually see an unbalanced amount of load (number of users attached to a base station) on the macro base station in comparison to the small base station. This imbalance is responsible for hampering the quality of experience for the users connected to macro base station as it leads to degradation in their received data rates because the users are now competing for the fixed resource (bandwidth) at the base station. It also leads to underutilization of resources at the small base station, since they are powered up and running far below their maximum load capacity.

To mitigate this issue 3GPP suggests a technique called Cell Range Expansion (CRE). Utilizing this technique the small cell base stations can increase their Reference Signal Receive Power (RSRP) value such that they are more attractive (in terms of signal strength) than the macro base station for their nearby users. Finding the exact value for this bias is not a straightforward task as the bias value changes with various system parameters like load at base station and distance between the user and the base station [26].

Depending on the implementation, user association algorithms can be categorised as follows:

**Centralized user association algorithms:** Requires a central controller (often co-located with macro base station) that has the complete overview of a large region comprising of macro as well as small base stations. A centralized static framework to study the relation of user association and resource allocation in HetNet (focusing on global proportional fairness metric) was proposed in [37]. Co-channel deployment, orthogonal deployment and partially shared/overlap deployment (shown in table 2.1)

| Channel Allocation Scheme | Overview |
|---|---|
| Co-Channel Deployment (CCD) | In this scheme all the available M sub-channels are used by the macro as well as pico base stations. |
| Orthogonal Deployment (OD) | In this scheme the pico base station uses k sub-channels, while the macro base station uses M-k sub-channels. |
| Partial Overlap Deployment (POD) | In this scheme the macro base station shares k sub-channels with the pico base station while transmitting at a lower power in the shared sub-channels to reduce interference. Remaining M-k sub-channels are used solely by the macro base station. |

Table 2.1: Types of channel allocation schemes

were considered as three channel allocation strategies for a comparative analysis. A drawback of the centralized scheme is the presence of a single point of failure (central controller) that can lead to the disruption of load balancing for the overall system.

**Distributed user association algorithms:** Often runs independently at each base station (macro or pico) in a distributed manner i.e. each base station is responsible for deciding which users it wants to serve. These association schemes usually encounter a large amount of information exchange due to their distributed and iterative nature. They are also highly susceptible to minute changes in the base station load. A distributed algorithm for user association focusing on load balancing in HetNet, optimizing a logarithmic utility function (for network-wide proportional fairness) of long term rate for each user was provided in [26].

On the basis of run time granularity, user association algorithms can be classified into following two categories:

**Online user association algorithm [30]:** These set of algorithms solve the user association problem in a dynamic environment i.e. in the presence of spatial-temporal variation in user signal strength. They can further be subdivided into:

- Periodic online user association algorithms - These algorithms run periodically after a fixed period of time.
- Trigger-based online user association algorithms - These algorithms run only when a certain predefined event has occurred.

**Offline user association algorithm [37]:** These algorithms solve the user association problem in a static environment considering a snapshot (for a particular time instance) of the overall system.

Formulating and solving user association problems using convex optimization techniques for networks with modest size and complexity becomes computationally intensive especially for their real time implementation. Thus a low-complexity heuristic based association scheme [33] (showing performance close to optimal schemes) is preferable for deployment in a real-world scenario.

## 2.4 Energy Efficiency

Energy efficiency of a cellular network is often described by the ratio of system level throughput to system level power consumption. Two prominent technologies that aid in enhancing the energy efficiency are small cells and massive MIMO. Small cells improve the performance of the network by reducing the distance between the base station and the user, thereby improving the SNR and energy efficiency [38]. We often face a trade-off while deploying small cells as adding more small cells increases the static part of power consumption which is not in our control, thus we aim to reduce the dynamic part (load dependent) by as much as possible. Power consumption can also be reduced by switching some of the small cells to sleep mode. Massive MIMO improves the energy efficiency by adding more antennas at the base station and using sophisticated techniques like beamforming allowing spatial multiplexing of users and/or higher SNR.

Recent works like [39] have studied the impact of base station equipped with renewable energy supply in a HetNet environment. Such base stations are often focused on using the harvested energy to the fullest rather than the traditional on-grid power supply. A low complexity centralized green energy aware user association scheme that offloads users from base stations having low green energy to ones having larger green energy (without violating the minimum data rate for each user) was presented in [33].

# Chapter 3

# System Model

## 3.1 System Assumptions

We make the following assumptions for our system model:

- Analysis is done on the downlink signal because a macro base station, uses 87% of its total power consumption for downlink communication but only 13% is used for uplink [40].

- All the users are stationary (when the snapshot of the system is observed) and automatically attach to the macro base station when pico base stations are fully loaded or in sleep/turned off mode.

- Macro base station and pico base stations (with non-overlapping coverage area) transmit at different frequencies to avoid cross-tier interference.

- For simplification purpose, perfect backhaul and channel conditions (in the absence of fast fading) are assumed for the duration of the algorithm.

- All the base stations are considered to be active/switched on. They are transmitting at all times with their maximum transmit power (fixed and known a priori).

- Macro base station cannot be overloaded i.e. it can support all the users present in the system. The maximum load capacity for the pico base station is assumed to be 1/macro_pico_load_factor [41, 42].

- A user can only be associated to a single base station and each base station divides its allocated bandwidth equally among its users.

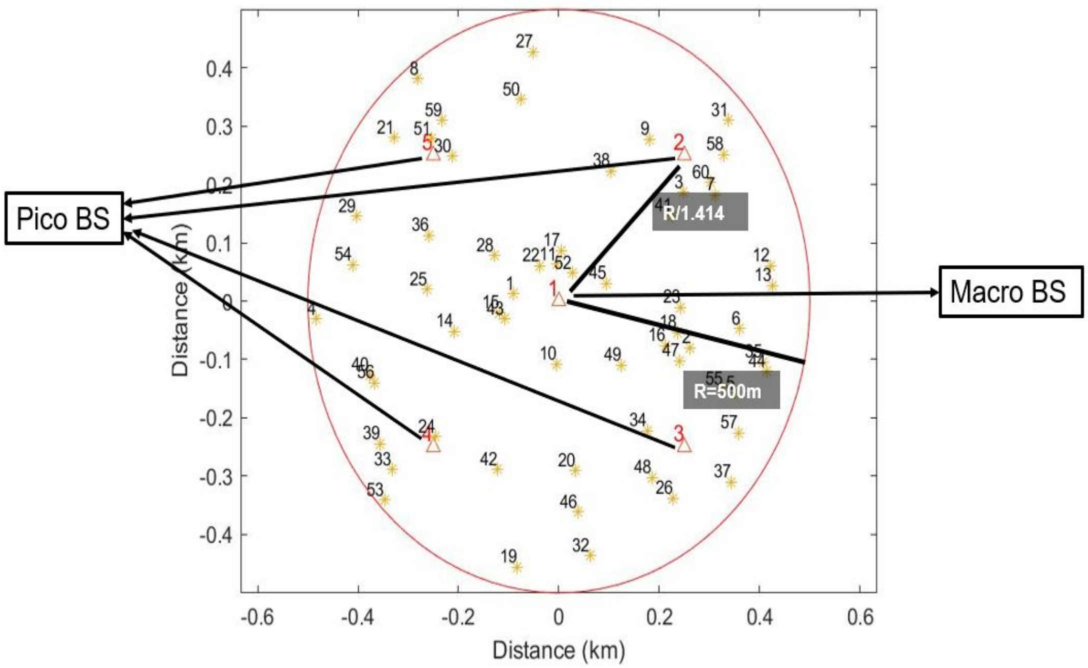


Figure 3.1: Simulation network topology

## 3.2 System Model

Limitations of the ns-3 simulator platform for studying end-to-end simulations of cellular networks has been studied extensively [43]. P. Alvarez *et al.* [44] provides a comparative analysis of the existing dense small cell network simulators. Based on these works, we selected MATLAB as our simulation environment for evaluating the performance of various user association algorithms. Some of the important characteristics of our simulation model include macro base station as well as pico base stations (open-access) having omnidirectional antenna. The coverage area for macro base station is assumed to be circular with 500m radius. Slow fading is modelled as log normal shadowing. Small scale fading parameters have been neglected as the user association schemes analysed here are assumed to be running on a larger timescale and on averaged (instead of instantaneous) channel state information.

Figure 3.1 depicts the network topology used for our simulation for a random single run. A similar topology is used throughout the project for analyzing the performance of various user association algorithms for 200 simulation runs each.

**Algorithm 1** SNR Calculation Algorithm

```
Input: P_BS, dista, shadowFadingBS, shadowFadingRealizations, noiseFloordBm_Macro, P_SC, shadowFadingSC, noiseFloordBm_SC
Output: SNR
for k in each user do
  for j in each base station do
    if j equals 1 then
      SNR(j,k) = P_BS - (128.1+37.6*log10(dista(j)) + shadowFadingBS *shadowFadingRealizations(j,k,iter) ) - noiseFloordBm_Macro
    else
      SNR(j,k) = P_SC - (140.7+36.7*log10(dista(j)) + shadowFadingSC *shadowFadingRealizations(j,k,iter) ) - noiseFloordBm_SC
    end if
  end for
end for=0
```

The system consists of 60 users randomly distributed across the coverage region (red circle) of the macro base station. Base stations are denoted by red triangles with macro base station represented by triangle having number 1 (located at the center of red circle) with coverage radius of R = 500m. Pico base stations are represented by triangles having numbers 2, 3, 4 and 5. They are located at a distance of R/1.414 from the macro base station. For all the simulation runs, we have considered the positions of the base stations to be fixed and the users to be static (for each individual run). Table 3.1 summarizes the simulation parameters [45, 46].

Algorithm 1 shows the SNR calculation algorithm that we have used to calculate the SNR for each user in our simulation. In the algorithm, $K_r$ denotes the total number of users in the system and $K_t$ denotes the total number of base stations in the system. For each user, we calculate its distance from all the base stations, which is stored in the array - dista. The statement j equals 1 refers to the condition for computing the SNR between a specific user and the macro base station. We have used P_BS to represent the maximum transmit power of the macro base station, and P_SC represents the maximum transmit power of the pico base station. Other parameters related to their respective path loss model and log normal shadowing have been taken from [45] and [46]. After calculating the SNR, Shannon-Hartley theorem is used to get the maximum possible data rate for communication between the user and a base station.

| ATTRIBUTE | VALUE |
|---|---|
| Users | 60 |
| Simulation iterations | 200 |
| Macro BS | 1 |
| Pico BS | 4 |
| Macro BS radius | 500 m |
| Transmit power (Macro BS) | 46 dBm |
| Transmit power (Pico BS) | 30 dBm |
| Bandwidth (Macro BS) | 10 MHz (50 RB) |
| Bandwidth (Pico BS) | 20 MHz (100 RB) |
| Antenna model | Isotropic |
| Noise floor (Macro BS) | -99 dBm |
| Noise floor (Pico BS) | -95.9897 dBm |
| Path loss model (Macro BS) | 128.1+37.6*log10(R) R in km |
| Path loss model (Pico BS) | 140.7+36.7*log10(R) R in km |
| Shadow fading Macro BS (Log normal shadowing) | 8 dB (Standard deviation) |
| Shadow fading Pico BS (Log normal shadowing) | 8 dB (Standard deviation) |
| Minimum distance between user and Macro BS | 35 m |
| Minimum distance between user and Pico BS | 10 m |
| Carrier frequency (Macro BS) | 2 GHz |
| Carrier frequency (Pico BS) | 3.5 GHz |
| macro_pico_load_factor ($L_{\mathrm{f}}$) | 5 |

Table 3.1: Simulation parameters. Legend: BS = Base Station, RB = Resource Blocks

## 3.3 Performance Evaluation Metrics

In this section, we provide explanation for some of the frequently used performance evaluation metrics.

### 3.3.1 Fairness

Fairness is an important metric which comes up often while performing system level analysis. In its usual sense fairness ensures that the users involved in the system are receiving a fair share of total available system resources. Fairness can be described and evaluated using the following measurement metrics:

**Jain's Fairness Index:** Jain's fairness index is a popular metric used to define and measure fairness. It is defined as:

$$J\left(R_1, ...R_n, ...R_N\right) = \frac{\left(\sum_{n=1}^{N} R_n\right)^2}{N\left(\sum_{n=1}^{N} \left(R_n\right)^2\right)} \tag{3.1}$$

where,

$N$ − Number of users

$R_n$ − Throughput of $n$-th user

According to the equation 3.1, the index value lies in the range 1/N (worst case) to 1 (best case). When the value of the index is close to 1, it signifies that all the users in the system are getting equal throughput. A major drawback with this index is that even if all the users are getting equal rate there might be several users whose demand is less than the rate they are receiving. This leads to decline of system resources.

**User Requirement Satisfaction (URS):** In this approach if the network is able to meet each users demand then the network is said to be fair to all the users. For implementation purposes we could bin different data demands into predefined categories of video traffic, VoIP traffic etc. Another variation to this can be the approach where the network decides and provides each user with a predetermined minimum data rate.

**Max-min fairness:** The main idea behind max-min fairness is to first fulfill the demand of the user with the minimum requirement of resources, then fulfill subsequent demands (arranged in increasing order of their requirement). For example, if the requirements for 4 users are: [2, 2.5, 4, 5] and the total available resources are 10, the max-min fairness would allocate resources in the following way:

Iteration 1: [2.5, 2.5, 2.5, 2.5]

Iteration 2: [2, 2.66, 2.66, 2.66]

Iteration 3: [2, 2.66, 2.7, 2.7]

### 3.3.2 System Throughput

A trivial approach, for increasing the total system throughput, is to drop the users with the lowest signal strength (users near the edge of the network coverage) since they are

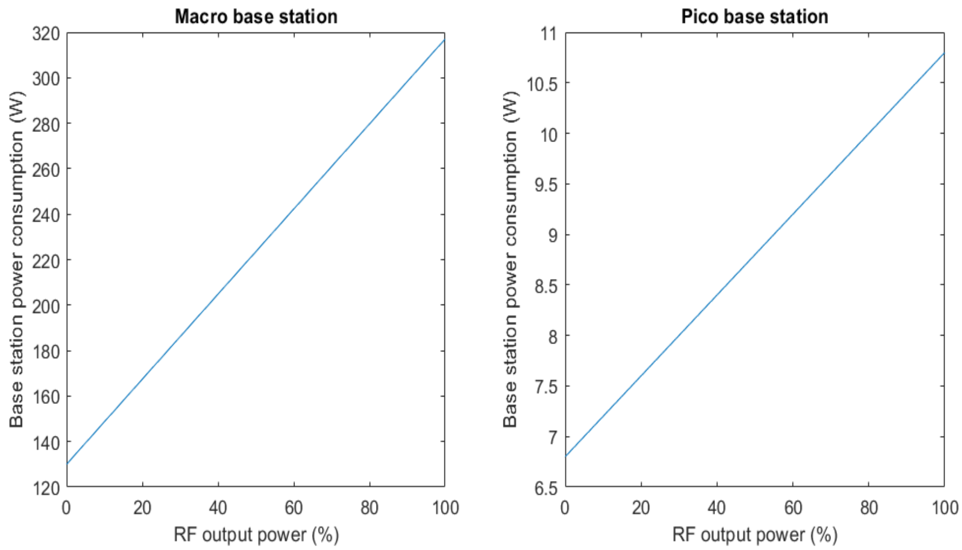


Figure 3.2: Power consumption Vs relative RF output power for macro and pico base station (based on values from table 3.3)

utilizing resources of the base station which could have been given to another user with better signal strength. But this approach will not be fair to the users with lowest signal strength. In order to be fair to all the users we can divide the resources (bandwidth at the base station) equally amongst all of them but that would not result in the maximum system throughput. A potential solution to this issue is to maximize the logarithmic utility function [24, 26] instead of linear utility function due to its concave nature and load balancing properties. It also helps in achieving network-wide proportional fairness by providing more resources to users with lower signal strength than those who receive a good signal.

### 3.3.3 System Power Consumption

From figure 3.2, we observe that the power consumption for a macro base station is much larger in comparison to a pico base station [3, 47]. This is because a major chunk of macro base station's power consumption comes from the power amplifier. However, for the pico base station, baseband processing is the largest power consuming entity. Active cooling is required only in the case of macro base station, pico base stations use natural air circulation as a cooling mechanism. A linear trend in power consumption is more prominent in the case of macro/micro base stations [48]. For a pico base station,

| NOTATIONS | DEFINITION |
|---|---|
| $N_{\text{TRX}}$ | Number of transceiver chains (i.e. transmit/receive antennas per site) |
| $P_{\text{max}}$ | Maximum RF output power at maximum load |
| $P_0$ | Power consumption at the minimum non - zero output power |
| $\Delta_{\text{p}}$ | Slope of load dependent power consumption |
| $P_{\text{out}}$ | Base station RF output power |
| $P_{\text{in}}$ | Base station power consumption |
| $P_{\text{sleep}}$ | Sleep mode power consumption |

Table 3.2: Notations used in equation 3.2

| Parameters | Macro base station | Pico base station |
|---|---|---|
| $N_{\text{TRX}}$ | 1 | 1 |
| $P_0$ | 130 W | 6.8 W |
| $\Delta_{\text{p}}$ | 4.7 | 4.0 |
| $P_{\text{max}}$ | 39.8 W (46 dBm) | 1.0 W (30 dBm) |

Table 3.3: Power consumption model parameter values for base stations

we find that the power consumption can be considered as almost constant. The total transmit power consumption for a base station comprises of two parts, the first part is the static part which depends on transceiver hardware and the second is the dynamic part which depends on the transmitted signal and number of antennas at the base station (number of Tx-Rx chains). Therefore, the overall system power consumption also depends on the optimal count and the placement of these base stations. The following equation models the linear relation between base station power consumption and base station Radio Frequency (RF) output power:

$$P_{\text{in}} = \left\{ \begin{array}{ll} N_{\text{TRX}}.\left(P_0 + \Delta_{\text{p}}.P_{\text{out}}\right) & 0 < P_{\text{out}} \leq P_{\text{max}} \\ N_{\text{TRX}}.P_{\text{sleep}} & P_{\text{out}} = 0 \end{array} \right\} \tag{3.2}$$

Recent works [33] on reducing the system power consumption focus on reducing the on-grid power consumption in cellular networks by using green energy i.e. equipping the base stations with solar panels. By reducing the on-grid power consumption dependency, they help in reducing $CO_2$ emissions (which is often a major contributor for global warming). The authors propose a heuristic based association algorithm to offload users from base stations having lower green energy to base stations with excessive

| Value | Macro base station | Pico base station |
|---|---|---|
| Minimum power consumption (1% load) | 131.87 W | 6.84 W |
| Maximum power consumption (100% load) | 317.06 W | 10.8 W |

Table 3.4: Energy consumption range for base stations

green energy, since solving the optimization problem formulated by them to obtain the optimal user association was NP-Hard.

# Chapter 4

# User Association Algorithms

## 4.1 Max-SNR based User Association Algorithm

The previous chapter explains the procedure for calculating the SNR's between all the base stations and user pairs, now we implement our baseline user association algorithm, max-SNR based association. In this scheme, a user is associated to the base station from which it receives the highest SNR i.e. the user attaches itself to the base station from which it receives the strongest signal. Algorithm 2 describes the detailed steps for its implementation.

**Algorithm 2** Max-SNR based user association algorithm

**Input:** SNR, SNR_first, curr_load_max_SNR, max_load
**Output:** x
**for** *i in each user* **do**
  **for** *j in each base station* **do**
    **if** SNR(j,i) *equals* SNR_first(1,i) **and** *current base station's load* < *maximum load* **then**
      x(j,i) = 1
      curr_load_max_SNR(j) = curr_load_max_SNR(j) + 1
    **else if** SNR(j,i) *equals* SNR_first(1,i) **and** *current base station's load* >= *maximum load* **then**
      x(1,i) = 1
      curr_load_max_SNR(1) = curr_load_max_SNR(1) + 1
    **else**
      x(j,i) = 0
    **end if**
  **end for**
**end for**=0

The array SNR_first stores the maximum SNR value for each user (amongst all its received SNR's from all the base stations). The variable x denotes the user association matrix, curr_load_max_SNR array stores the current load (number of users attached) at each base station and max_load stores the maximum permissible load for each base station.

Going through all the possible SNR's for a particular user, if any particular SNR matches with the maximum SNR for that user and the current load at base station is less than its maximum load, we set the association matrix as 1 for that particular user base station pair. If the base station having the best SNR is fully loaded then we attach the user to the macro base station. Otherwise, we set the association value as 0 for that user and base station pair. After obtaining the user association matrix (considering all the users) we use Shannon's capacity formula to calculate each user's maximum throughput.

## 4.2 Load Balancing based User Association Algorithm

Several association schemes for HetNet are represented by Fig. 2. in [26]. It highlights the challenges faced using a max-SNR (similar to max-SINR scheme depicted in the figure) based association scheme. From the figure, we observe that this scheme leads to a heavily loaded macro base station (shown in the figure by the point from where all the blue lines originate). This leads to the following major issues:

- Underutilization of resources at the pico base stations because most of the users are attached to the macro base station (even the users within the range of pico base station).

- Degradation in the QoS of the users attached to the macro base station because the bandwidth at the macro base station is fixed and an increase in the number of users leads to more users competing for it. This leads to a reduction in the share of bandwidth allocated to each attached user.

The above drawbacks motivated the need for designing a load balancing based user association algorithm that tries to balance load amongst macro and pico base stations by shifting users from macro base station to pico base stations. This scheme would also lead to an increase in the overall system throughput because with the reduction of load at the macro, users attached to it will experience a throughput gain. Also, the shifted

| NOTATIONS | DEFINITION |
|---|---|
| $R_{ij}$ | Maximum throughput of user $i$ attached to base station $j$ |
| $B_j$ | Bandwidth of the base station $j$ |
| $R_{ij\,\text{min}}$ | Minimum throughput supported by user $i$ attached to base station $j$ |
| $\text{SNR}_{ij}$ | Signal-to-Noise Ratio of user $i$ attached to base station $j$ |
| $N_{\text{TRX}}$ | Number of transceiver chains (i.e. transmit/receive antennas per site) |
| $P_{\text{out}}$ | Base station RF output power |
| $P_{\text{in}}$ | Base station power consumption |
| $P_{\text{sleep}}$ | Sleep mode power consumption |
| $P_{\text{max}}$ | Maximum RF output power at maximum load |
| $\Delta_{\text{p}}$ | Slope of load dependent power consumption |
| $P_0$ | Power consumption at the minimum non - zero output power |
| $\mathbb{U}$ | Set of all users $\{U_1, U_2, ...\}$ |
| $\mathbb{B}$ | Set of all base stations $\{M, S_1, S_2, ...\}$ |
| $x_{ij}$ | User association matrix |
| $K_r$ | Total number of users in the system |
| $K_t$ | Total number of base stations in the system |
| $L_{\text{f}}$ | $\left(\frac{\text{Maximum load capacity of macro base station}}{\text{Maximum load capacity of pico base station}}\right)$ |

Table 4.1: Notations used throughout the thesis

users might experience a gain in their throughput as they are now attached to the pico base station having larger bandwidth than macro thus leading to an efficient use of the available system resources.

To implement the load balancing scheme [26], we formulate the following optimization equation.

$$\begin{aligned}
&\max_x \quad \left(\sum_{i\in\mathbb{U}}\sum_{j\in\mathbb{B}} x_{ij}\log\left(\frac{R_{ij}}{\sum\limits_{k\in\mathbb{U}} x_{kj}}\right)\right) && \\
&\text{subject to} \quad \sum_{j\in\mathbb{B}} x_{ij} = 1, && \forall i \in \mathbb{U} \\
&\qquad\qquad 0 \le x_{ij} \le 1, && \forall i \in \mathbb{U}, and\ \forall j \in \mathbb{B} \\
&\qquad\qquad \sum_{k\in\mathbb{U}} x_{kj} \le \left(\frac{K_r}{L_{\text{f}}}\right), && \forall j \in \mathbb{B}\backslash M \\
&\text{where,} && \\
&R_{ij} = B_j \log_2(1 + \text{SNR}_{ij}) &&
\end{aligned} \tag{4.1}$$

Table 4.1 describes the notations along with their definitions used in this thesis. In equation 4.1, the term $\sum\limits_{k\in\mathbb{U}} x_{kj}$ signifies the load at base station $j$. Here, the load is measured by the number of users attached to a base station.

The first constraint ensures that a user can only be connected to a single base station.

The second constraint is a relaxed association constraint where 0 signifies no association and 1 signifies full association. Ideally, the association variable should be a binary variable. But the association problem becomes combinatorial in nature due to this binary association variable. Its complexity for the brute force association algorithm is $\Theta\left((K_t)^{K_r}\right)$ [26]. Solving this computation becomes nearly impossible for even a modest-sized network. Further, the exact optimization problem with binary association constraint is NP-hard. Thus, in order to mitigate this issue, [26] uses the relaxation which allows the association variable to take any real value from 0 to 1. The physical significance of this relaxation is that it allows the users to be attached to more than one base station, i.e. "Fractional User Association". After solving the convex optimization equation 4.1 using the CVX [49], we can get the final user association matrix by rounding up the values to either 0 or 1.

The last constraint is regarding the maximum load capacity of the pico base stations (maximum number of users that can be attached to the pico base station).

## 4.3 Power Minimization based User Association Algorithm

From figure 13 in [47], we observe that the power consumption for macro base station is much larger as compared to the pico base station. The total energy distribution for macro base station, indicates that its power consumption can be modelled using a linear equation. Similar equations can also be used for pico but the power consumption for pico base station is almost constant [47].

The following equation models the linear power consumption behaviour of a base station [48].

$$P_{\text{in}} = \left\{ \begin{array}{ll} N_{\text{TRX}}.\left(P_0 + \Delta_{\text{p}}.P_{\text{out}}\right) & 0 < P_{\text{out}} \leq P_{\text{max}} \\ N_{\text{TRX}}.P_{\text{sleep}} & P_{\text{out}} = 0 \end{array} \right\} \tag{4.2}$$

| Parameters | Macro base station | Pico base station |
|---|---|---|
| $N_{\mathrm{TRX}}$ | 1 | 1 |
| $P_0$ | 130 W | 6.8 W |
| $\Delta_{\mathrm{p}}$ | 4.7 | 4.0 |
| $P_{\max}$ | 39.8 W (46 dBm) | 1.0 W (30 dBm) |

Table 4.2: Power consumption model parameter values for base stations

From table 4.2, we can infer that reducing the load on the macro base station by shifting users from macro to pico base station, would result in a large reduction in the total system level power consumption. The ratio of the base station RF output power to the maximum RF output power is a measure of the load of a base station.

$$\frac{\text{Load at base station}}{\text{Maximum load at base station}} = \frac{P_{\mathrm{out}}}{P_{\max}} \tag{4.3}$$

Thus the final equation for power consumption minimization can be given as follows:

$$\begin{aligned}
\max_x \quad & -\sum_{j\in\mathbb{B}} \left( \left( \frac{\sum_{i\in\mathbb{U}} x_{ij}}{K_r} P_{\max_j} \Delta_{\mathrm{p}_j} \right) + P_{0_j} \right) && \\
\text{subject to} \quad & 0 \le x_{ij} \le 1, && \forall i \in \mathbb{U}, and\ \forall j \in \mathbb{B} \\
& \sum_{j\in\mathbb{B}} x_{ij} = 1, && \forall i \in \mathbb{U} \\
& \sum_{j\in\mathbb{B}} x_{ij} R_{ij} \ge R_{ij\,\min}, && \forall i \in \mathbb{U} \\
& \sum_{k\in\mathbb{U}} x_{kj} \le \left( \frac{K_r}{L_{\mathrm{f}}} \right), && \forall j \in \mathbb{B}\backslash M
\end{aligned} \tag{4.4}$$

Note, for the above mentioned optimization equation we maximize the negative sum of the power consumption for all the base stations, which is the same as minimizing the total system level power consumption.

The first constraint is a relaxed association constraint where 0 signifies no association and 1 signifies full association. The second constraint ensures that a user can be connected only to a single base station. The third constraint ensures that each user in the system gets a minimum predetermined data rate. This constraint is necessary because without it the solution of the equation might attach all users to the pico base stations (to reduce power consumption even if a user's data rate is severely impacted).

The last constraint guarantees that none of the pico base stations is overloaded.

## 4.4 E-ASSOC User Association Algorithm

In this section, we focus on improving the system level energy efficiency. User association algorithms maximizing the system throughput (log objective function for proportional fairness) with load balancing while transmitting at full power on the allocated sub-channels and implementing user association constraints have been extensively studied in [37]. Association schemes minimizing the power consumption of the system while satisfying QoS requirements of each user, power constraints at the base stations and user association constraints have been considered in [10, 33].

From the analysis of load balancing based association scheme and the power minimization based association scheme, we find that in order to achieve the above metrics (to improve energy efficiency) we need to offload users from macro base station to pico base station.

The equation below represents the optimization equation used for improving energy efficiency.

$$
\begin{aligned}
&\max_x \quad \left( \frac{\sum\limits_{i\in\mathbb{U}}\sum\limits_{j\in\mathbb{B}} x_{ij}\log\left(\frac{R_{ij}}{\sum\limits_{k\in\mathbb{U}} x_{kj}}\right)}{-\sum\limits_{j\in\mathbb{B}}\left(\left(\frac{\sum\limits_{i\in\mathbb{U}} x_{ij}}{K_r} P_{\max_j}\Delta_{\mathrm{p}_j}\right)+P_{0_j}\right)} \right) \\
&\text{subject to} \quad 0 \le x_{ij} \le 1, && \forall i \in \mathbb{U}, and\ \forall j \in \mathbb{B} \\
&\qquad \sum_{j\in\mathbb{B}} x_{ij} = 1, && \forall i \in \mathbb{U} \\
&\qquad \sum_{j\in\mathbb{B}} x_{ij}R_{ij} \ge R_{ij\,\min}, && \forall i \in \mathbb{U} \\
&\qquad \sum_{k\in\mathbb{U}} x_{kj} \le \left(\frac{K_r}{L_{\mathrm{f}}}\right), && \forall j \in \mathbb{B}\backslash M \\
&\text{where,} \\
&R_{ij} = B_j \log_2\left(1+\mathrm{SNR}_{ij}\right)
\end{aligned}
\tag{4.5}
$$

The previous association schemes, we know how to solve the numerator and the denominator separately. Figure 4.1 shows some of the existing approaches used for solving such problem. Amongst all the mentioned approaches, we focus on the heuristic based

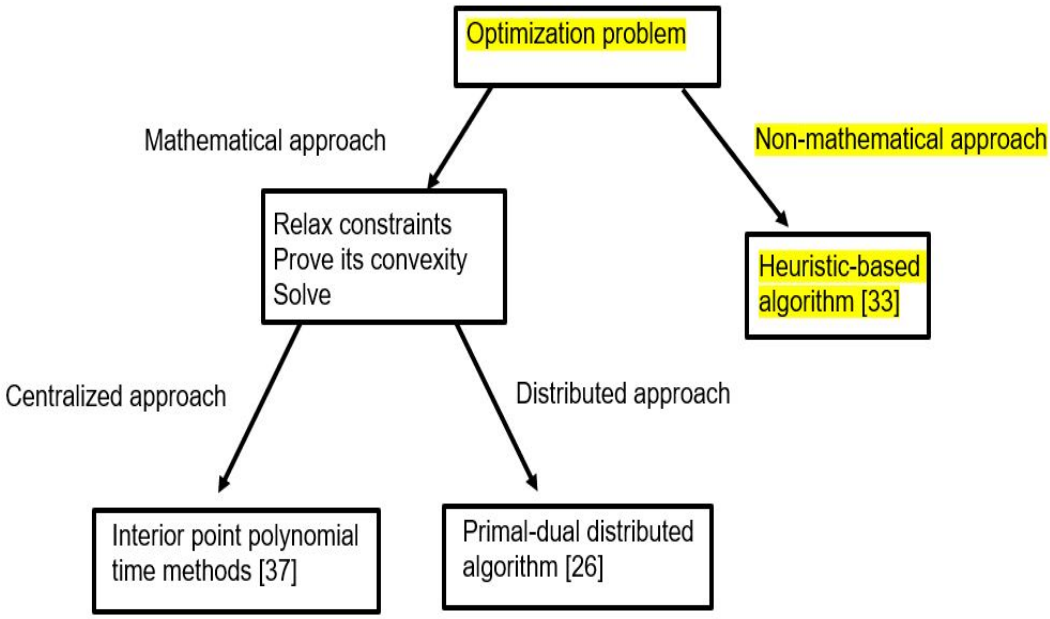


Figure 4.1: Summary of approaches used for solving optimization equation

solution (by traversing the highlighted path) due to its low computation complexity.

Based on our understanding from previous association schemes, in order to improve the performance of the system we need to shift users from the macro to the pico base station. Thus, users whose performance doesn't degrade severely after shifting from macro to pico base station are the best candidate for offloading. Using the above mentioned information, algorithm 3 describes the details of our proposed E-ASSOC algorithm.

In this association scheme, a user attaches itself to the base station providing the second best SNR if the difference between the best and the second best SNR is less than a pre-determined threshold value. The array SNR_first stores the maximum SNR value (amongst its received SNR's from all the neighboring base stations) for each user. The array SNR_second stores the second maximum SNR value for each user.

Going through all the possible SNR's for a particular user, if the difference between best two SNR values lies below our threshold and current SNR value is the second-best SNR value then we set the association matrix entry as 1 for that user base station pair. Else if, the difference between top two SNR values is greater than the threshold and the current SNR value is best SNR value, we set the association matrix as 1. Otherwise, we set the value to be zero.

**Algorithm 3** E-ASSOC user association algorithm

```
Input: SNR, SNR_first, SNR_second, curr_load_heur, max_load, threshold_val
Output: x
for i in each user do
  for j in each base station do
    if SNR(j,i) equals SNR_first(1,i) and current base station's load < maximum
    load  and j is pico base station  then
      x(j,i) = 1
      curr_load_heur(j) = curr_load_heur(j) + 1
    else if SNR(j,i) equals SNR_first(1,i) and current base station's load >= max-
    imum load  and j is pico base station then
      x(1,i) = 1
      curr_load_heur(1) = curr_load_heur(1) + 1
    else if SNR(j,i) equals SNR_second(1,i) and current base station's load < max-
    imum load  and j is pico base station and (SNR_first(1,i) - SNR_second(1,i))
    <= threshold_val then
      x(j,i) = 1
      curr_load_heur(j) = curr_load_heur(j) + 1
    else if SNR(j,i) equals SNR_second(1,i) and current base station's load
    >= maximum load  and j is pico base station and (SNR_first(1,i) -
    SNR_second(1,i)) <= threshold_val then
      x(1,i) = 1
      curr_load_heur(1) = curr_load_heur(1) + 1
    else if SNR(j,i) equals SNR_first(1,i) and j is macro base station and
    (SNR_first(1,i) - SNR_second(1,i)) > threshold_val then
      x(1,i) = 1
      curr_load_heur(1) = curr_load_heur(1) + 1
    else
      x(j,i) = 0
    end if
  end for
end for=0
```

# Chapter 5

# Evaluation Results

In this section, we investigate the results obtained from the implementation of user association algorithms described in the previous chapter.

| | Max-SNR algorithm | Load balancing algorithm | Power minimization algorithm with QoS requirements ($R_{ij\,\min} = 100$ Mbps) |
|---|---|---|---|
| System throughput (Mbps) | 630.0245 | 849.989 | 798.817 |
| System power consumption (W) | 339.234 | 227.288 | 207.9399 |
| Energy efficiency (Mbit/Joule) | 1.857 | 3.739 | 3.8415 |

Table 5.1: Max-SNR Vs Load balancing Vs Power minimization user association algorithms

Table 5.1 provides us with an average results of different system level metrics for three user association algorithms averaged over 200 simulation runs.

Load balancing scheme provides a higher system throughput (improvement of 34.91%) than the max-SNR scheme. Power minimization schemes also performs better than the max-SNR scheme in terms of total system throughput. Amongst all the implemented association schemes, it has the least system power consumption (63.14% reduction in comparison to baseline max-SNR scheme) because the main objective for this scheme was minimizing the system level power consumption. For evaluation purposes, we have assumed $R_{ij\,\min}$ to be 100 Mbps. This value is calculated by allocating the total bandwidth available at respective base station prior to any association.

Table 5.2 shows a comparison between the baseline max-SNR scheme and our proposed E-ASSOC association scheme. We have selected the value of threshold to be 30 dB. This particular value for the threshold was selected to achieve system throughput comparable to load balancing scheme. We can clearly notice a gain of 41.26% in the

| | Max-SNR algorithm | E-ASSOC algorithm (threshold_val = 30 dB) |
|---|---|---|
| System throughput (Mbps) | 630.0245 | 889.965 |
| System power consumption (W) | 339.234 | 255.134 |
| Energy efficiency (Mbit/Joule) | 1.857 | 3.488 |

Table 5.2: Max-SNR Vs E-ASSOC user association algorithm

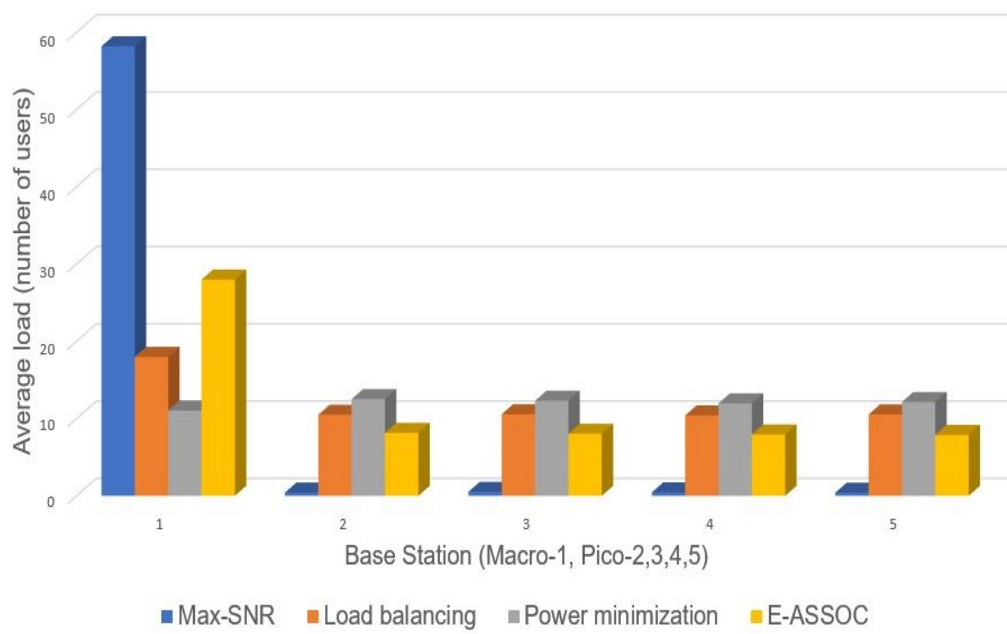


Figure 5.1: Load at each base station after execution of user association algorithms

system throughput as well as a reduction of 32.96% in the system power consumption. These results can be attributed to the fact that our heuristic based E-ASSOC scheme was designed to reduce the load at the macro base station and increase the utilization of pico base stations by offload users from macro to pico base station. Another key observation is that the results from E-ASSOC association scheme lies somewhere between the results obtained from max-SNR association scheme and the other optimization equation based association schemes. This reinforces that fact that E-ASSOC user association scheme is not as good as the optimal scheme but shows similar performance enhancement. Ultimately, a gain of 87.83% in energy efficiency was obtained over the baseline max-SNR scheme.

Figure 5.1 shows the final load at each base station (after execution of association

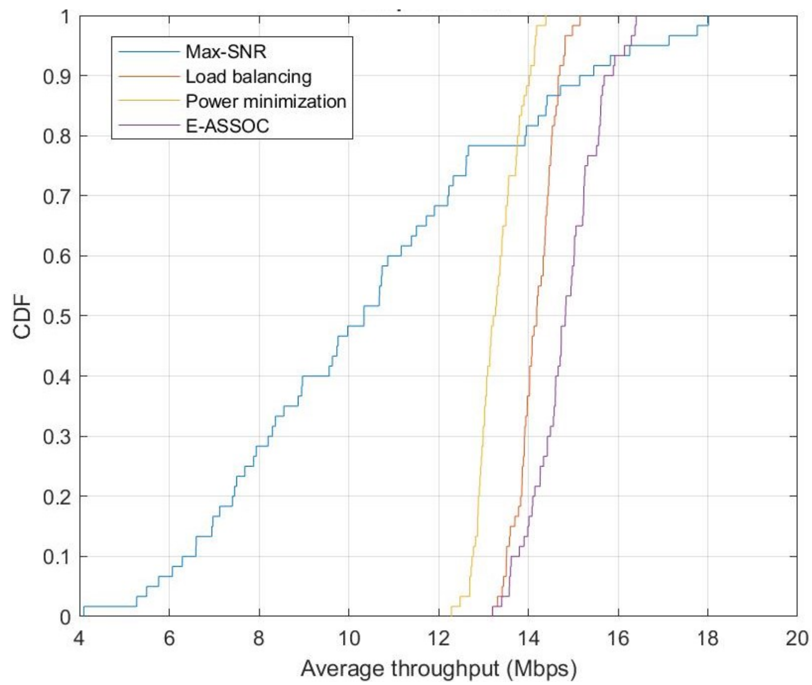


Figure 5.2: Comparison of average user throughput for all user association algorithms considering 200 simulation runs (60 users per run)

| | Max-SNR algorithm | Load balancing algorithm | Power minimization algorithm |
|---|---|---|---|
| Mean user throughput (Mbps) | 10.50 | 14.17 | 13.31 |
| Jain's Fairness Index (JFI) | 0.90756 | 0.99906 | 0.99873 |

Table 5.3: Mean user throughput and JFI analysis for Max-SNR Vs Load balancing Vs Power minimization user association algorithms

algorithm) for all the user association schemes. We notice a large spike in the load at macro base station for the max-SNR scheme since most of the users receive a strong signal from the macro base station (due to its high transmit power). Load balancing and power minimization schemes show a much more balanced load distribution. This is because both the schemes optimize metrics that are benefited from macro to pico base station user offloading. E-ASSOC scheme also shows load balancing results similar to optimization based schemes as it has the concept of user offloading baked into it.

Figure 5.2 depicts the Cumulative Distribution Function (CDF) of user throughput for all the schemes. From the plot, we find that all three schemes (except max-SNR scheme) perform better than our baseline max-SNR scheme since more than 50% of users in the other schemes have a higher throughput in comparison to max-SNR scheme.

| | Max-SNR algorithm | E-ASSOC algorithm |
|---|---|---|
| Mean user throughput (Mbps) | 10.50 | 14.83 |
| Jain's Fairness Index | 0.90756 | 0.99738 |

Table 5.4: Mean user throughput and JFI analysis for Max-SNR vs E-ASSOC user association algorithms

From Table 5.3, observing the JFI values for all the different schemes, we find that the load balancing scheme has the best JFI value. This means that the load balancing scheme allocates the system resources most fairly amongst all the other schemes as it uses network-wide proportional fairness as its optimization metric. Power minimization scheme is not as good as the load balancing scheme in terms of fairness but has a very close value. Max-SNR scheme is the least fair amongst all the schemes. In terms of mean user throughput, load balancing and power minimization algorithms show significant improvement over the baseline max-SNR based association algorithm.

A comparative study of the E-ASSOC scheme and the baseline max-SNR scheme is shown in table 5.4. The values indicate superior performance of the E-ASSOC scheme over the max-SNR scheme for both mean user throughput as well as overall network-wide fairness.

# Chapter 6

# Conclusion and Future Work

## 6.1 Conclusion

In this work, we proposed and evaluated a centralized heuristic based user association algorithm (E-ASSOC) to enhance the energy efficiency of HetNet over the existing baseline max-SNR association algorithm. Design of our algorithm was based on the insights obtained from existing optimization based association schemes. Results show that the proposed E-ASSOC scheme achieves a gain of 87.83% in energy efficiency (bits/Joule) relative to baseline scheme.

## 6.2 Future Work

This sections emphasises on some of future areas for further exploration.

- **Mobile users:** All the association schemes analysed in this work were based on a snapshot of the network i.e. considering static user positions. However, there is a need to evaluate the schemes with mobile users taking interference into account.
- **Linear Fractional Programming:** The heuristic scheme proposed in this work is often considered as a non-mathematical solution. It would be interesting to compare its performance with the final optimization equation (for energy efficiency) using a more rigorous mathematical approach.
- **Evaluation for 5G systems:** The simulation environment considered throughout this work utilized path loss models from 3GPP LTE specification. With rapidly emerging 5G standards, it becomes important to asses the performance of these algorithms on the latest standards.

# Bibliography

[1] Ericsson, "Ericsson mobility report," 2019. [Online]. Available: https://www.ericsson.com/4acd7e/assets/local/mobility-report/documents/2019/emr-november-2019.pdf

[2] J. Malmodin and D. Lundén, "The electricity consumption and operational carbon emissions of ict network operators 2010-2015," 2018.

[3] G. Auer, V. Giannini, C. Desset, I. Godor, P. Skillermark, M. Olsson, M. A. Imran, D. Sabella, M. J. Gonzalez, O. Blume *et al.*, "How much energy is needed to run a wireless network?" *IEEE Wireless Communications*, vol. 18, no. 5, pp. 40–49, 2011.

[4] D. Feng, C. Jiang, G. Lim, L. J. Cimini, G. Feng, and G. Y. Li, "A survey of energy-efficient wireless communications," *IEEE Communications Surveys & Tutorials*, vol. 15, no. 1, pp. 167–178, 2012.

[5] Ericsson, "Breaking the energy curve report," 2020. [Online]. Available: https://www.ericsson.com/495d5c/assets/local/about-ericsson/sustainability-and-corporate-responsibility/documents/2020/breaking-the-energy-curve-report.pdf

[6] ——, "A technical look at 5g energy consumption and performance," 2019. [Online]. Available: https://www.ericsson.com/en/blog/2019/9/energy-consumption-5g-nr

[7] D. Raychaudhuri, I. Seskar, G. Zussman, T. Korakis, D. Kilper, T. Chen, J. Kolodziejski, M. Sherman, Z. Kostic, X. Gu *et al.*, "Challenge: Cosmos: A city-scale programmable testbed for experimentation with advanced wireless," in

*Proceedings of the 26th Annual International Conference on Mobile Computing and Networking*, 2020, pp. 1–13.

[8] B. A. Bjerke, "Lte-advanced and the evolution of lte deployments," *IEEE Wireless Communications*, vol. 18, no. 5, pp. 4–5, 2011.

[9] M. Xiao, S. Mumtaz, Y. Huang, L. Dai, Y. Li, M. Matthaiou, G. K. Karagiannidis, E. Björnson, K. Yang, I. Chih-Lin *et al.*, "Millimeter wave communications for future mobile networks," *IEEE Journal on Selected Areas in Communications*, vol. 35, no. 9, pp. 1909–1935, 2017.

[10] E. Björnson, M. Kountouris, and M. Debbah, "Massive mimo and small cells: Improving energy efficiency by optimal soft-cell coordination," in *ICT 2013*. IEEE, 2013, pp. 1–5.

[11] D. Liu, L. Wang, Y. Chen, M. Elkashlan, K.-K. Wong, R. Schober, and L. Hanzo, "User association in 5g networks: A survey and an outlook," *IEEE Communications Surveys & Tutorials*, vol. 18, no. 2, pp. 1018–1044, 2016.

[12] N. Docomo, "Performance of eicic with control channel coverage limitation," *R1-103264, 3GPP Std., Montreal, Canada*, 2010.

[13] J. G. Andrews, "Seven ways that hetnets are a cellular paradigm shift," *IEEE Communications Magazine*, vol. 51, no. 3, pp. 136–144, 2013.

[14] H. Shokri-Ghadikolaei, C. Fischione, G. Fodor, P. Popovski, and M. Zorzi, "Millimeter wave cellular networks: A mac layer perspective," *IEEE Transactions on Communications*, vol. 63, no. 10, pp. 3437–3458, 2015.

[15] I. Guvenc, "Capacity and fairness analysis of heterogeneous networks with range expansion and interference coordination," *IEEE Communications Letters*, vol. 15, no. 10, pp. 1084–1087, 2011.

[16] A. Khandekar, N. Bhushan, J. Tingfang, and V. Vanghi, "Lte-advanced: Heterogeneous networks," in *2010 European wireless conference (EW)*. IEEE, 2010, pp. 978–982.

[17] K. Okino, T. Nakayama, C. Yamazaki, H. Sato, and Y. Kusano, “Pico cell range expansion with interference mitigation toward lte-advanced heterogeneous networks,” in *2011 IEEE International Conference on Communications Workshops (ICC)*. IEEE, 2011, pp. 1–5.

[18] H.-S. Jo, Y. J. Sang, P. Xia, and J. G. Andrews, “Outage probability for heterogeneous cellular networks with biased cell association,” in *2011 IEEE Global Telecommunications Conference-GLOBECOM 2011*. IEEE, 2011, pp. 1–5.

[19] Q. Ye, M. Al-Shalash, C. Caramanis, and J. G. Andrews, “On/off macrocells and load balancing in heterogeneous cellular networks,” in *2013 IEEE global communications conference (GLOBECOM)*. IEEE, 2013, pp. 3814–3819.

[20] R. Bendlin, V. Chandrasekhar, R. Chen, A. Ekpenyong, and E. Onggosanusi, “From homogeneous to heterogeneous networks: A 3gpp long term evolution rel. 8/9 case study,” in *2011 45th Annual Conference on Information Sciences and Systems*. IEEE, 2011, pp. 1–5.

[21] E. Bjornson, E. A. Jorswieck, M. Debbah, and B. Ottersten, “Multiobjective signal processing optimization: The way to balance conflicting metrics in 5g systems,” *IEEE Signal Processing Magazine*, vol. 31, no. 6, pp. 14–23, 2014.

[22] R. Q. Hu and Y. Qian, “An energy efficient and spectrum efficient wireless heterogeneous network framework for 5g systems,” *IEEE Communications Magazine*, vol. 52, no. 5, pp. 94–101, 2014.

[23] L. Su, C. Yang, Z. Xu, and A. F. Molisch, “Energy-efficient downlink transmission with base station closing in small cell networks,” in *2013 IEEE International Conference on Acoustics, Speech and Signal Processing*. IEEE, 2013, pp. 4784–4788.

[24] T. Bu, L. Li, and R. Ramjee, “Generalized proportional fair scheduling in third generation wireless data networks,” in *IEEE INFOCOM*, 2006, pp. 1–12.

[25] R. Jain, *The art of computer systems performance analysis: techniques for experimental design, measurement, simulation, and modeling.* John Wiley & Sons, 1990.

[26] Q. Ye, B. Rong, Y. Chen, M. Al-Shalash, C. Caramanis, and J. G. Andrews, "User association for load balancing in heterogeneous cellular networks," *IEEE Transactions on Wireless Communications*, vol. 12, no. 6, pp. 2706–2716, 2013.

[27] M. Kim, S. Y. Jung, and S.-L. Kim, "Sum-rate maximizing cell association via dual-connectivity," in *2015 International Conference on Computer, Information and Telecommunication Systems (CITS).* IEEE, 2015, pp. 1–5.

[28] C. Rosa, K. Pedersen, H. Wang, P.-H. Michaelsen, S. Barbera, E. Malkamaki, T. Henttonen, and B. Sébire, "Dual connectivity for lte small cell evolution: Functionality and performance aspects," *IEEE Communications Magazine*, vol. 54, no. 6, pp. 137–143, 2016.

[29] S. Sadr and R. S. Adve, "Handoff rate and coverage analysis in multi-tier heterogeneous networks," *IEEE Transactions on Wireless Communications*, vol. 14, no. 5, pp. 2626–2638, 2015.

[30] Z. Li, C. Wang, and C.-J. Jiang, "User association for load balancing in vehicular networks: An online reinforcement learning approach," *IEEE Transactions on Intelligent Transportation Systems*, vol. 18, no. 8, pp. 2217–2228, 2017.

[31] M. Yousefvand, K. Hamidouche, and N. B. Mandayam, "Learning-based resource optimization in ultra reliable low latency hetnets," *arXiv preprint arXiv:1905.04788*, 2019.

[32] S. Zhang, S. Zhao, M. Yuan, J. Zeng, J. Yao, M. R. Lyu, and I. King, "Traffic prediction based power saving in cellular networks: A machine learning method," in *Proceedings of the 25th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems*, 2017, pp. 1–10.

[33] Q. Fan and N. Ansari, "Green energy aware user association in heterogeneous networks," in *2016 IEEE wireless communications and networking conference.* IEEE, 2016, pp. 1–6.

[34] A. Damnjanovic, J. Montojo, Y. Wei, T. Ji, T. Luo, M. Vajapeyam, T. Yoo, O. Song, and D. Malladi, "A survey on 3gpp heterogeneous networks," *IEEE Wireless communications*, vol. 18, no. 3, pp. 10–21, 2011.

[35] A. K. Mishra, D. Mallick, M. Issar, and P. Singh, "Performance analysis of dual-hop df relaying systems in the combined presence of cee and rfi," in *2017 9th International Conference on Communication Systems and Networks (COMSNETS).* IEEE, 2017, pp. 354–359.

[36] 3rd Generation Partnership Project, "3GPP TR 36.912 V2.0.0 - Feasibility study for Further Advancements for EUTRA (Release 9))," Tech. Rep., 2009.

[37] D. Fooladivanda and C. Rosenberg, "Joint resource allocation and user association for heterogeneous wireless cellular networks," *IEEE Transactions on Wireless Communications*, vol. 12, no. 1, pp. 248–257, 2012.

[38] J. Hoydis, M. Kobayashi, and M. Debbah, "Green small-cell networks," *IEEE Vehicular Technology Magazine*, vol. 6, no. 1, pp. 37–43, 2011.

[39] T. Zhang, H. Xu, D. Liu, N. C. Beaulieu, and Y. Zhu, "User association for energy-load tradeoffs in hetnets with renewable energy supply," *IEEE Communications Letters*, vol. 19, no. 12, pp. 2214–2217, 2015.

[40] C. Desset, B. Debaillie, V. Giannini, A. Fehske, G. Auer, H. Holtkamp, W. Wajda, D. Sabella, F. Richter, M. J. Gonzalez *et al.*, "Flexible power modeling of lte base stations," in *2012 IEEE wireless communications and networking conference (WCNC).* IEEE, 2012, pp. 2858–2862.

[41] J.-C. Nanan and B. Stern, "Small cells call for scalable architecture," *Freescale white paper*, 2012.

[42] T. Nguyen, "Small cell networks and the evolution of 5g (part 1)," 2017. [Online]. Available: https://www.qorvo.com/design-hub/blog/small-cell-networks-and-the-evolution-of-5g

[43] T. Zugno, M. Polese, M. Lecci, and M. Zorzi, "Simulation of next-generation cellular networks with ns-3: Open challenges and new directions," in *Proceedings of the 2019 Workshop on Next-Generation Wireless with ns-3*, 2019, pp. 38–41.

[44] P. Alvarez, C. Galiotto, J. van de Belt, D. Finn, H. Ahmadi, and L. DaSilva, "Simulating dense small cell networks," in *2016 IEEE Wireless Communications and Networking Conference*. IEEE, 2016, pp. 1–6.

[45] 3rd Generation Partnership Project, "3GPP TR 36.814 - Further advancements for E-UTRA physical layer aspects (Release 9)," Tech. Rep., 2010.

[46] ——, "3GPP TR 36.842 - Study on Small Cell enhancements for E-UTRA and E-UTRAN; Higher layer aspects (Release 12)," Tech. Rep., 2013.

[47] G. Auer, O. Blume, V. Giannini, I. Godor, M. Imran, Y. Jading, E. Katranaras, M. Olsson, D. Sabella, P. Skillermark *et al.*, "D2. 3: Energy efficiency analysis of the reference systems, areas of improvements and target breakdown," *Earth*, vol. 20, no. 10, 2010.

[48] D. Liu, Y. Chen, K. K. Chai, T. Zhang, and M. Elkashlan, "Two-dimensional optimization on user association and green energy allocation for hetnets with hybrid energy sources," *IEEE Transactions on Communications*, vol. 63, no. 11, pp. 4111–4124, 2015.

[49] M. Grant, S. Boyd, and Y. Ye, "Cvx: Matlab software for disciplined convex programming," 2009.