JOINT OPTIMIZATION OF CELL ZOOMING, SCHEDULING AND USER ASSOCIATION

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ABSTRACT

JOINT OPTIMIZATION OF CELL ZOOMING, SCHEDULING AND USER ASSOCIATION

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Capacity can be increased by employing small cells in future mobile networks. When small cells are considered, a large number of base stations have to be deployed. This approach enlarges network infrastructures and increases the amount of energy consumption. Traffic demand in a mobile network is not fixed in time or space, and it cannot be accurately predicted in advance. Network functions such as base station scheduling, cell zooming or user-to-base-station association can be dynamically controlled to conserve energy. Base station scheduling is defined as deciding whether or not to keep a base station active depending on traffic demand. The coverage area of a base station can be adapted to demand that is referred to as cell zooming. User-to-base-station association can be dynamically configured to adjust the load of base stations for reducing energy consumption. Most of the related work in the literature consider these problems separately. In this thesis, we present a joint base station scheduling, zooming and user association technique. The major contribution of this thesis is reducing power consumption by turning off redundant base stations and adapting transmit power of active base stations to network conditions for maintaining quality of service and satisfying users. We formulated the joint optimization problem with the objective of reducing energy consumption and enhancing user satisfaction. We validated the proposed technique by using MATLAB optimization toolbox. In this work, we reduced energy consumption by 47% in comparison to the state-of-the-art solution.

Keywords: Dynamic Network Optimization, Power Optimization, Mobile Edge Computing, Linear Programing, MATLAB Optimization Toolbox

ÖZ

ORTAKLAŞA HÜCRE ZUMLAMA, ÇİZELGELEME VE KULLANICI İLİŞKİLENDİRME

Çalık, Mert
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Kapasite, gelecekteki mobil ağlarda küçük hücreler kullanılarak artırılabilir. Küçük hücreler düşünüldüğünde, çok sayıda baz istasyonunun konuşlandırılması gerekir. Bu yaklaşım, ağ altyapılarını genişletmekte ve enerji tüketimini artırmaktadır. Bir mobil şebekedeki trafik talebi zaman ya da mekanda sabit değildir ve önceden tam olarak tahmin edilemez. Baz istasyonu çizelgeleme, hücre zumlama veya kullanıcı-baz istasyon ilişkilendirmesi gibi ağ işlevleri enerjiyi korumak için dinamik olarak kontrol edilebilir. Baz istasyonu çizelgeleme, trafik talebine bağlı olarak bir baz istasyonunun aktif kalıp kalmamasına karar verme olarak tanımlanır. Bir baz istasyonunun kapsama alanı, hücre zumlama olarak adlandırılan yöntemle talebe göre uyarlanabilir. Kullanıcı-baz istasyonu ilişkilendirmesi, enerji tüketimini azaltmak ve baz istasyonlarının yükünü ayarlamak için dinamik olarak yapılandırılabilir. Literatürdeki ilgili çalışmaların çoğu bu problemleri ayrı ayrı ele almaktadır. Bu tezde, bir ortaklaşa baz istasyonu planlama, zumlama ve kullanıcı ilişkilendirme çözümü sunuyoruz.

Bu tezin ana katkısı, gereksiz baz istasyonlarını kapatarak ve aktif baz istasyonlarının aktarım gücünü, servis kalitesini korumak ve kullanıcıları tatmin etmek için şebeke koşullarına göre adapte ederek güç tüketimini azaltmaktır. Ortaklaşa optimizasyon problemini, enerji tüketimini azaltmak ve kullanıcı memnuniyetini artırmak amacıyla formüle ettik. Önerilen tekniği MATLAB optimizasyon aracını kullanarak doğruladık. Bu çalışmada, en son çalışmalardan birine göre enerji tüketimini %47 oranında düşürdük.

Anahtar Kelimeler: Dinamik Ağ Optimizasyonu, Enerji Optimizastonu, Mobil Kenar Hesaplama, Doğrusal Programlama, MATLAB Optimizasyon Araç Kutusu

To my family

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LIST OF ABBREVIATIONS

BS	Base Station
CDMA	Code Division Multiple Access
CPU	Central Processing Unit
CQI	Channel Quality Indication
DNO	Dynamic Network Optimization
EE	Energy Efficiency
GA	Genetic Algorithm
GPRS	General Packet Radio Service
GSM	Global System for Mobile Communications
ICT	Information and Communication Technology
IoT	Internet of Things
LTE	Long Term Evolution
MEC	Mobile Edge Computing
MMS	Multi Media Messages
MNO	Mobile Network Optimization
MS	Mobile Station
PA	Power Amplifier
PS	Pattern Search Polling Algorithm
QoS	Quality of Service
RAN	Radio Access Network
RF	Radio Frequency
SA	Simulated Annealing Algorithm
SINR	Signal-to-Interference-plus-Noise Ratio
SO	Particle Swarm Optimization Algorithm
UE	User Equipment
WWWW	Wireless World Wide Web
1G	First-Generation
2G	Second-Generation

3G	Third-Generation
4G	Fourth-Generation
5G	Fifth-Generation

CHAPTER 1

INTRODUCTION

1.1 Scope and Motivation

Nearly 3% of the world's energy is consumed by information and communication technology (ICT) infrastructures, which accounts for about 2% of the carbon dioxide (CO_2) emissions worldwide [6]. This phenomenon directly causes an increase in greenhouse gas emissions, which poses a major threat to the environment [7].

In current and especially in future networks, a large number of base stations (BS) are required due to the exponential growth in traffic load. Base stations comprise the biggest share of energy costs in a cellular network, as it is shown in Figure 1.1 [3].

Mobile network architectures are predominantly dimensioned for excessive traffic load scenarios. Networks have relentlessly working BSs in order to satisfy the quality of service (QoS) and mobile coverage requirements. Practically, network devices are often over equipped with excessive capacity because the actual traffic load is subjected to high traffic load variations during a normal daily operation cycle. Consequently, a lot of BSs are being under-utilized for most of the time, and as a result, enormous amounts of energy are wasted without generating considerable workload.

Base stations are always operational by default in existing cellular networks. However, service traffic throughout day and night and service traffic in urban and rural areas are obviously different. This causes a great waste of energy. As a result, the focus towards the energy consumption of the wireless access network infrastructures is being shifted by the evolving movement towards energy-efficient network operation.

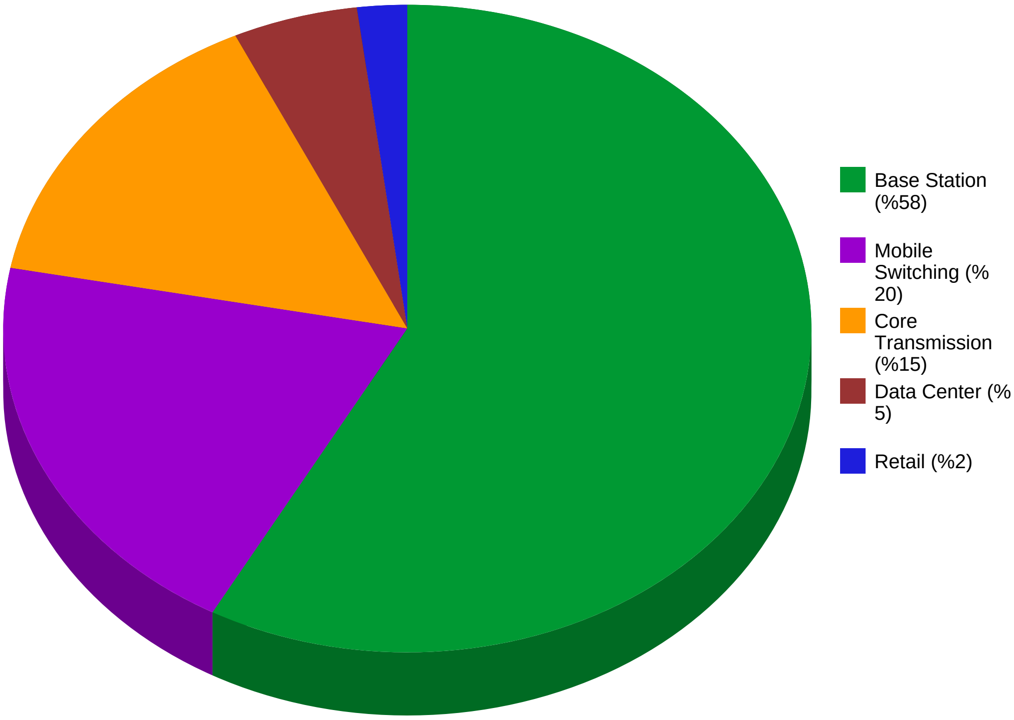

Figure 1.1: The distribution of power consumption in cellular networks (redrawn from [3].)

Therefore, in the design of the fifth-generation (5G) wireless communications, high energy efficiency (EE) is becoming a primary concern and saving energy is predominantly positioning itself at the forefront of system design. However, 5G mobile networks should minimize power consumption subject to some quality-of-service requirements.

1.2 Problem Definition

It is extensively known that in the coming years, wireless networks will have larger economical and ecological impact. This argument affects both the environment and the economy. As a result, an innovative research discipline called "green cellular networks" that focuses on the environmental impacts of cellular networks has been created. The term "green" in the name of the discipline represents the attempts to reducing avoidable greenhouse gases (e.g., CO_2) emissions. Also, from mobile operators' perspective, this term mostly means to provide additional financial interests, especially by cutting down operational expenses related to the energy costs [3].

Power optimization should be dealt with as an important problem for the future networks, as regards the current networks and technology development. Minimizing the power usage, while improving the network performance is a big challenge [8].

Table1.1: Power consumption distribution in cell radio access equipments [1].

Equipment	Power Consumption
Power Amplifier	50-80 % ($\sim$ 1200 W)
Air Conditioning	10-25 % ($\sim$ 300 W)
Signal Processing (Analog/Digital)	5-15 % ($\sim$ 200 W)
Power Supply	5-10 % ($\sim$ 100 W)

Today's classic power consumption distribution in base stations can be seen in Table 1.1. The largest portion of energy is mainly consumed in the network instruments such as power amplifiers (PAs) and air conditioning systems. To conserve energy, new energy-aware network dimensioning solutions that consider temporal and spatial variations of traffic load should be proposed [1].

Current cellular systems require manual configuration and network management, which is costly, time-consuming and error-prone due to the ever-increasing rate of mobile users and nodes. This leads to self-regulation capabilities for network management with minimal human involvement. Moreover, since mobile end users continue to use network resources as they move from one cell to another, the traffic load within cells will be changed continuously, therefore the configuration must be adaptive to the network conditions.

Self-organization and self-optimization of networks are important points in the future cellular networks. In the current network optimization and planning tasks, the autonomous administration is desired to reduce the massive need of human efforts. For instance, in order to achieve higher network performance, BSs need to adapt their operational parameters such as transmit power, antenna alignment to the system dynamics such as traffic and environmental changes. In practice, self-regulation and optimization will help to improve overall QoS and coverage in the network and it reduces system capital and operational costs [9].

As a result, in recent years, Mobile Network Optimization (MNO) technologies have made enormous progress; and the Dynamic Network Optimization (DNO) approach appeared in the recent years, aiming to consistently optimize the network in reply to changes in network traffic and conditions [10]. The main objective of the MNO is to provide the best possible network design with the best possible QoS at the lowest cost. In order to achieve this, in the first step, the problem must be formulated.

1.3 Contributions

As the main contribution, a joint cell zooming, scheduling and user association technique is designed using mobile edge computing. As a result, this technique induces two sub-contributions.

The first contribution is significantly reducing the power consumption according to the basic model, where no power adaption and sleep scheduling are employed. The power consumption reduction occurs because in the proposed algorithm, the redundant BSs are turned off and active BSs adapt their transmit power based on network conditions.

The second contribution of this thesis is the enhancement with respect to a recent work [5]. In comparison to the work presented in [5], we enhance user satisfaction 47% by trading off a 5% increase in energy consumption since we consider outage probability in the proposed algorithm.

1.4 Outline

The rest of this thesis is organized as follows. Chapter 2 summarizes wireless technology generations, mobile edge computing, cell zooming and genetic algorithm, particle swarm algorithm, simulated annealing algorithm and pattern search polling algorithm of MATLAB Global Optimization Toolbox. The related work on the base station power optimization is explained briefly in Chapter 3. Chapter 4 contains the mathematical formulation of the problem and the related constraints. The simulation tool, implementation details and simulation results for different parameters are interpreted and compared with a recent work in Chapter 5. Finally, the thesis is concluded and the future works to be done are mentioned in Chapter 6.

CHAPTER 2

BACKGROUND

In this chapter, wireless technology generations, mobile edge computing, cell zooming and some of MATLAB Global Optimization Toolbox algorithms are summarized.

2.1 1G to 5G Wireless Technologies

In this section, evolution of wireless technologies from the first generation to the fifth generation is explained.

2.1.1 First Generation (1G)

1G refers to the first generation of wireless telephone technology. In 1980's, analog cellular systems such as the Total Access Communication System, the Advance Mobile Phone Service and the Nordic Mobile Telephone appeared as the first-generation (1G) systems [11]. Its speed was up to 2.4 kbps, wireless phones were used for voice only and it was allowing users to make voice calls in only one country. Some of the major drawbacks of this system were poor battery life, poor voice quality, no security, limited capacity, large phone size and poor handoff reliability.

2.1.2 Second Generation (2G)

In 1991 in Finland, the second generation of wireless telephone technology (2G) was launched. Its main standards are Global System for Mobile Communications (GSM), IS-13 and IS-95 [12]. Its data speed was up to 64 kbps. Its main improvements with respect to 1G were services such as text messages, multimedia messages (MMS), picture messages and providing better quality and capacity. Some of the major drawbacks of this system are requiring strong digital signals and being incapable of handling complex data like videos.

Then 2.5G technology which is the system between 2G and 3G cellular wireless had arisen. It was using 2g system framework but besides circuit switching, it applied packet switching. It provided data rate up to 144 kbps. By using General Packet Radio Service (GPRS) it provided connection to the Internet [13]. Apart from sending messages, browsing the web and sending e-mails were new features. Also, it supported a tiny camera on the phone.

2.1.3 Third Generation (3G)

3G technology refers to the third generation of mobile networks which was introduced in the 2000s. It increased data rate from 144 kbps to 2 Mbps. 3G is based on International Mobile Telecommunications 2000, a wideband CDMA (Code Division Multiple Access) standard, specified by the International Telecommunication Union [11]. Its main features are providing faster communication, send and receive large e-mail messages, video conferencing, more security, TV streaming and larger capacity. Some of the major drawbacks of this system were expensive fees for 3G license services and high bandwidth requirement.

2.1.4 Fourth Generation (4G)

4G technology refers to the fourth generation of network which was started from late 2000s. The main improvements of 4G are summarized in Table 2.1. 4G data rate can reach up to 1 Gbps. Services like data, voice, and multimedia are supplied to users on anywhere and anytime with high data rates with respect to the earlier generations. Applications like Digital Video Broadcasting, Multimedia Messaging Service, video chat and mobile TV are also accessible by users [14]. Therefore, one of the basic term used to describe 4G is MAGIC, which stands for:

- Mobile Multimedia,
- Anytime Anywhere,
- Global Mobility Support,
- Integrated Wireless Solution,
- Customized Personal Services.

On the other hand, some of the major drawbacks of this system are more battery usage, hardness of implementation, complicated hardware requirement and expensive equipment.

Table2.1: The basic differences between 3G and 4G [2].

Technology	3G	4G
Data Transfer Rate	3.1 MB/sec	100 MB/sec
Bandwidth	5-20 MHz	100 MHz
Frequency	1.6-2 GHz	2-8 GHz
Download and Upload	5.8 Mbps	14 Mbps

2.1.5 Fifth Generation (5G)

The next generation of wireless technology standards, 5G, started in the late 2010s. The 4G network soon will be replaced by the next generation 5G network to meet the increasing demand for high data rate [15]. This generation, also called as WWWW (Wireless World Wide Web), supports all wireless communications, without any limitation [13]. Green communication will play a major role in this system. New power optimization solutions should be produced to schedule time and frequency resources in order to maximize the efficiency upcoming systems. [16].

2.2 Mobile Edge Computing (MEC)

The QoS and data rate requirements of users are rapidly increasing. Although new mobile devices have more central processing unit (CPU) power, in a short time, even this will not be enough to handle the applications that need excessive processing [4]. As a result, Mobile Edge Computing (MEC) is introduced to reduce the network delay and provide context-aware services [17]. MEC is recognized as a promising paradigm in the next generation wireless networks, enabling the cloud-computing capabilities in close proximity to mobile devices [18], [19]. With the physical proximity, MEC realizes a low-latency connection to a large-scale resource-rich computing infrastructure by offloading the computation task to an adjacent computing server/cluster instead of relying on a remote cloud [20]. With MEC, the need for fast interactive response can be met within the network edge [21].

Mobile Edge Computing is a network architecture that enables IT and cloud-computing capabilities at the edge of the cellular network. MEC addresses this issue by placing the computing and storage resources closer to the Radio Access Network (RAN), to reduce the end-to-end latency, ensure better service delivery, and improve the user experience [22]. This technology is designed to be implemented at cellular base stations to provide rapid deployment of applications and other customer services.

The architecture of MEC is comprised of three essential elements: the hosting infrastructure management system, the application platform management system and the application management system. The hosting infrastructure management system consists of a virtualization manager and virtualization layer. The application platform system provides traffic control, radio access network information services, communication services, and service registry. The application management system is a virtualized machine for applications [23].

MEC offers a range of benefits, especially for operators, equipment providers, IT platform providers and system integrators. In addition to reducing the congestion of mobile core networks, MEC reduces the latency. Moreover, edge computing provides a way to collect and process information at local computer devices instead of in the cloud.

As it is illustrated in Figure 2.1, MEC has a lot of use cases. These use cases can be split into three main categories. MEC can be used for the consumer-oriented services like face recognition, augmented reality, image and video editing, gaming and remote desktop. The second category is QoS improvement services. Content caching and traffic monitoring can be given as example for this category. Finally, MEC can be utilized for third-party services like internet of things(IoT) and connected vehicles.

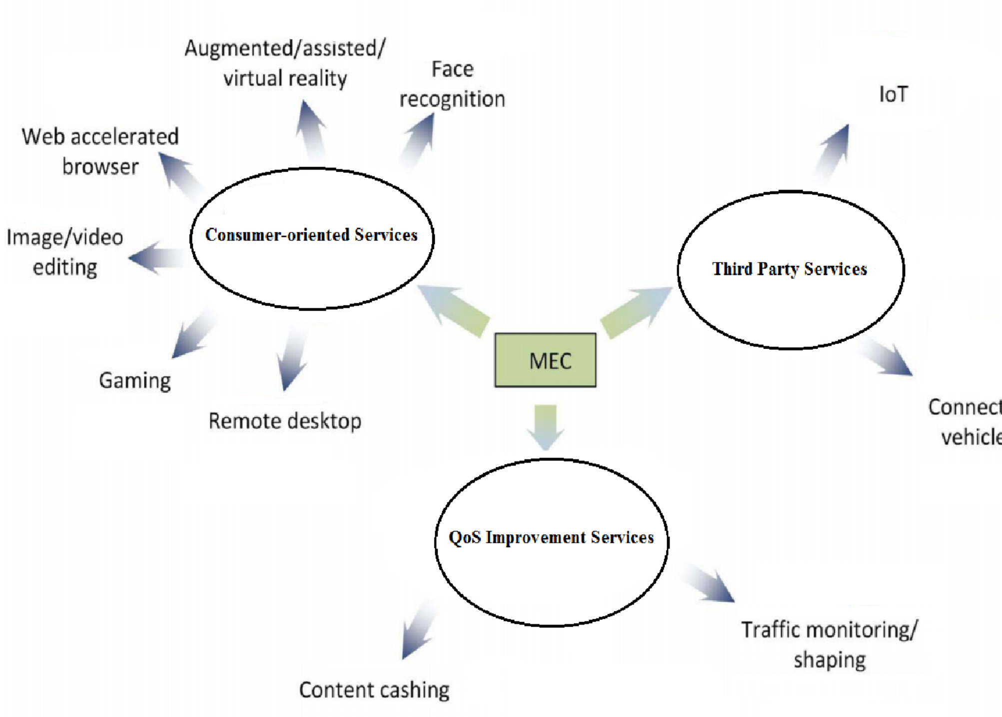

Figure 2.1: Example use cases and scenarios for MEC (redrawn from [4]).

2.3 Cell Zooming

In cellular networks, cell size is generally fixed depending on the estimated traffic load [24]. However, because of user mobility and variable characteristic of applications, in cellular networks, traffic load can have significant temporal and spatial fluctuations [25]. For instance, in a regular day, the wireless traffic in office areas is heavier than the wireless traffic in residential areas. Planning the network based on the maximum traffic load always make some of the cells under-utilized. Therefore, due to the instant changes in wireless traffic, static cell deployment is not appropriate. These changes in traffic load are felt more seriously in the smaller cells of next generation networks such as femto-cells, pico-cells and micro-cells and this situation makes the cell deployment harder [26].

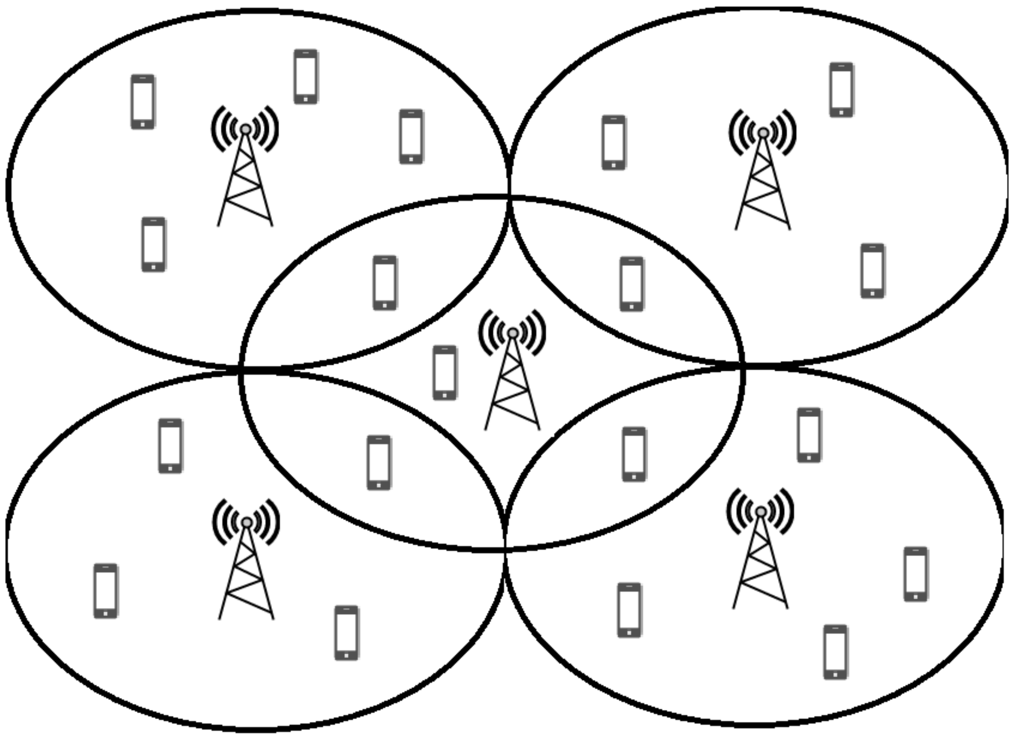

Figure 2.2: Original cells with BSs and users.

The most popular technique of cell zooming is increasing or decreasing base station transmit power. For instance, in an environment like in Figure 2.2, each cell have BSs and users.The BSs are located at the center of the cells. Cell zooming is zooming in the cell and reducing the size of the cell to cover only the users closer to the center of the cell like in Figure 2.3 and zooming out and increasing the size of the cell to cover a wider area like in Figure 2.4.

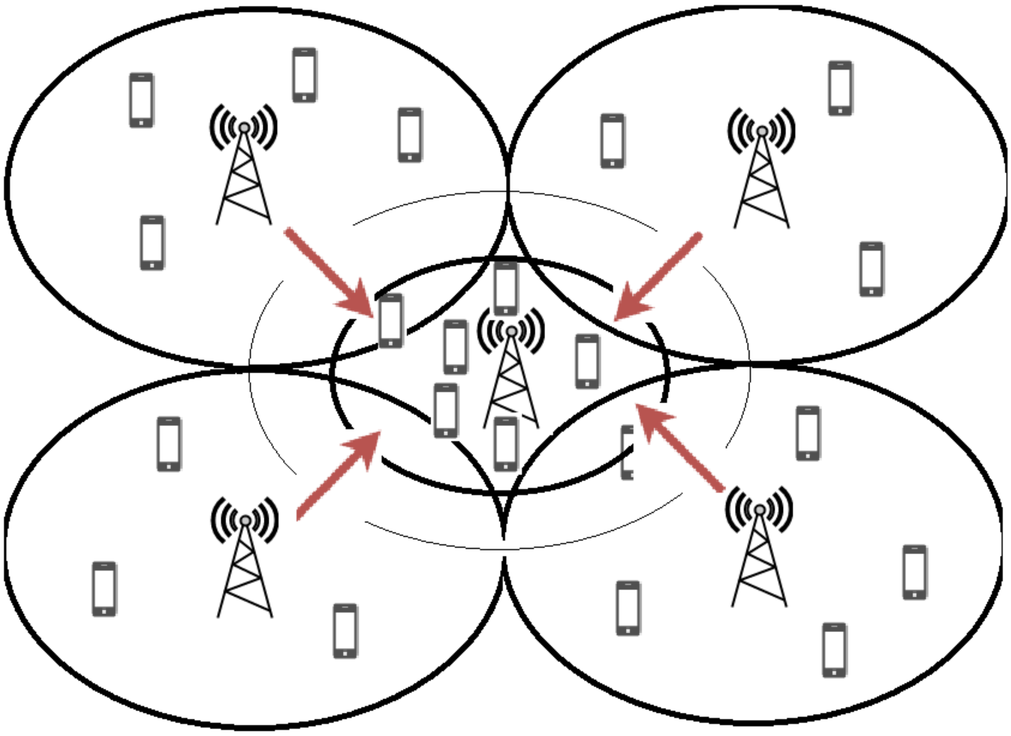

Figure 2.3: Cell zoom in by reducing coverage area.

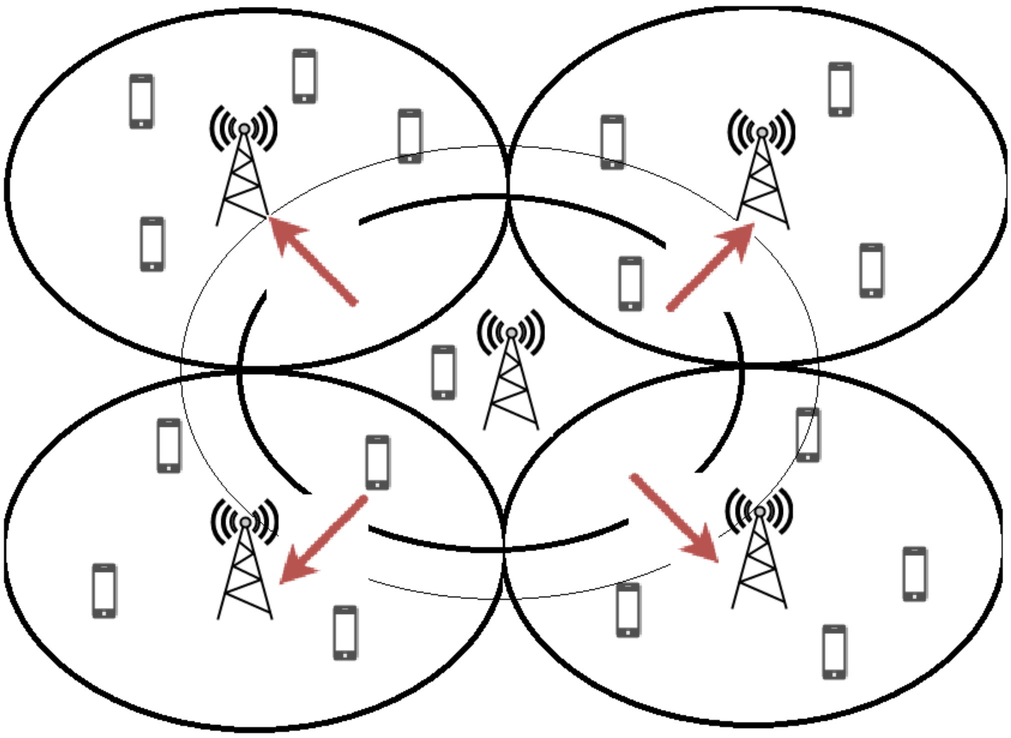

Figure 2.4: Cell zoom out by increasing coverage area.

2.4 MATLAB Global Optimization Toolbox

2.4.1 Genetic Algorithm

Genetic algorithm (GA) is a randomly determined optimization method that imitates the metaphor of biological evolution. GAs work on a possible population of solutions and apply the survival of the fittest principle to produce successively better estimates of a solution. In each generation of a GA, a new set of estimates is generated by selecting individuals according to their fitness levels in the problem domain and reproducing them with the help of the natural genetics operators. Like in natural adaptation, this process causes the evolution of population of individuals that are more suitable to the environment [27].

MATLAB has *ga* function in Global Optimization Toolbox that uses genetic algorithm to find the minimum value of a given function and this function works as follows [28], [29]:

1. The first step of the algorithm is creating a random initial population.
2. Then, the algorithm generates a sequence of new populations. It uses the current population to generate the next generation at each step. In order to generate the new generation, it performs the next steps:
    2.1. By their fitness values, that are called raw fitness scores, the algorithm scores the current population members.
    2.2. To convert the raw fitness scores into a more usable range, it scales these values. These scaled values are called expectation values.
    2.3. By using the expectation values, it selects parent members.
    2.4. Elite individuals that have lower fitness values in the current generation are selected and passed to the next generation
    2.5. Either by merging a pair of parent with each other or by mutating a single parent, the algorithm produces the children.
    2.6. Current population is replaced with the children to form the next generation.

3. When one of the stopping criteria is met, the algorithm stops.

2.4.1.1 Creating the Next Generation

The genetic algorithm uses the current generation to generate the children that form the next generation at each step. It chooses a set of individual from the current generation that is called parents to pass their genes to their children [30]. The algorithm usually selects individuals that have better fitness values as parents [31].

The genetic algorithm creates three types of children for the next generation:

- **Elite Children:** The individuals that have the best fitness values in the current population. They are passed to the next generation without any modification
- **Crossover Children:** The individuals that are generated by combining a pair of parents with each other.
- **Mutation Children:** The children that are created by mutating a single parent.

2.4.1.2 Stopping Conditions

The genetic algorithm uses the following thresholds to determine when to stop:

- **Generations:** The algorithm stops when the number of generations reaches to the generations value.
- **Time Limit:** The algorithm stops when the time limit value amount of time in seconds is passed since the beginning of the run.
- **Fitness Limit:** The algorithm stops when the value of the fitness function for the best point in the current population is less than or equal to fitness limit value.
- **Stall Generations:** The algorithm stops when the average relative change in the fitness function value less than function tolerance value for over stall generations amount of generations.

- **Stall Time Limit:** The algorithm stops when the average relative change in the fitness function value less than function tolerance value for over stall time limit amount of time in seconds.
- **Function Tolerance:** The algorithm stops when the average relative change in the fitness function value less than function tolerance value for over stall generations amount of generations.

2.4.2 Particle Swarm Optimization Algorithm

MATLAB has *particleswarm* function for particle swarm optimization algorithm (SO) that is designed based on the algorithm explained in [32] with the modifications recommended by [33] and [34]. This function works as follows [35], [36]:

1. The algorithm starts with creating the initial particles and assign initial velocities to these particles.
2. Then, the algorithm determines the minimum function value and the best location by evaluating the objective function at each particle location.
3. Based on the current velocity, the individual best locations of the particles and the best location of the neighbors, the algorithm determines new velocity values.
4. Iteratively, it updates the location of the particles by adding the velocity values to the old location and updates the velocities and neighbors.
5. When one of the stopping criteria is met, the algorithm stops.

2.4.2.1 Stopping Conditions

The particle swarm optimization algorithm uses the following thresholds to determine when to stop [37]:

- **Maximum Stall Iterations:** The algorithm stops when the average relative change in the objective function value less than function tolerance value for over maximum stall iterations amount of iterations.
- **Function Tolerance:** The algorithm stops when the average relative change in the objective function value less than function tolerance value for over maximum stall iterations amount of iterations.
- **Maximum Iterations:** The algorithm stops when the number of iterations reaches to the maximum iterations value.
- **Objective Limit:** The algorithm stops when the value of the objective function is less than or equal to objective limit value.
- **Maximum Stall Time:** The algorithm stops when the average relative change in the objective function value less than function tolerance value for over maximum stall time amount of time in seconds.
- **Maximum Time:** The algorithm stops when the maximum time value amount of time in seconds is passed since the beginning of the run.

2.4.3 Simulated Annealing Algorithm

MATLAB has *simulannealbnd* function for simulated annealing algorithm (SA) that is designed based on the algorithm explained in [38]. This function works as follows [39], [40]:

1. By using a probability distribution depending on the current temperature, the algorithm determines a distance value and selects a random trial point that is the distance value far away from the current point.
2. Then, the algorithm shifts the trial point with a uniformly random selected value within the violated bound.
3. The algorithm decides whether the new point is better or worse than the current point. If it is better, it becomes the next point, otherwise, based on the acceptance function, it still can mark this point as the next point.

4. It lowers the temperature methodically and stores the best point.
5. When one of the stopping criteria is met, the algorithm stops.

2.4.3.1 Stopping Conditions

The simulated annealing algorithm uses the following thresholds to determine when to stop [41]:

- **Stall Iteration Limit:** The algorithm stops when the average relative change in the objective function value less than function tolerance value for over stall iteration limit amount of iterations.
- **Function Tolerance:** The algorithm stops when the average relative change in the objective function value less than function tolerance value for over stall iteration limit amount of iterations.
- **Maximum Iterations:** The algorithm stops when the number of iterations reaches to the maximum iterations value.
- **Maximum Time:** The algorithm stops when the maximum time value amount of time in seconds is passed since the beginning of the run.
- **Objective Limit:** The algorithm stops when the value of the objective function is less than or equal to objective limit value.

2.4.4 Pattern Search Polling Algorithm

MATLAB has *patternsearch* function for pattern search polling algorithm (PS) that is designed based on the algorithm explained in [42] and [43]. This function works as follows [44]:

1. The pattern search starts at the start point value and calculate its objective function value.
2. At the first iteration, the mesh size is initial mesh size value.

3. The algorithm adds the pattern vectors to the initial point to compute the mesh points.
4. The algorithm polls the mesh points by computing their objective function values until it finds one whose value is smaller than the value of the current point.
5. If one of the mesh points has smaller objective function value, then the iteration is successful. Consequently, this point is set as the current point in the next iteration and the mesh size is multiplied with mesh expansion factor.
6. If none of the mesh points has smaller objective function value, then the iteration is unsuccessful. Consequently, the current point is not changed and the mesh size is multiplied with mesh contraction factor.
7. When one of the stopping criteria is met, the algorithm stops.

2.4.4.1 Stopping Conditions

The pattern search polling algorithm uses the following thresholds to determine when to stop [45]:

- **Mesh Tolerance:** The algorithm stops when the mesh size is less than the mesh tolerance value.
- **Maximum Iterations:** The algorithm stops when the number of iterations reaches to the maximum iterations value.
- **Maximum Time:** The algorithm stops when the maximum time value amount of time in seconds is passed since the beginning of the run.
- **Function Tolerance:** The algorithm stops when the change in the objective function in the previous two iterations is less than the function tolerance value.

CHAPTER 3

RELATED WORK

There are several works that try to find a solution for the base station power optimization problem. Different approaches are supported by each of these works. There are works that suggests to plan the network optimally before the construction, works that proposes distributed solution and works that recommends centralized solutions. BS sleep mode strategies and hybrid solutions are popular proposals among the centralized solutions.

3.1 Distributed Solutions

A distributed heuristic power control algorithm is proposed in [46]. It minimizes the total downlink power of an LTE system and increases the mean throughput for cell-edge users. In [46], each user sends Channel Quality Indication (CQI) feedback to the serving base stations. If the CQI value is less than a threshold, transmit power of the base station is increased a constant amount and decreased if the CQI value is higher than the threshold value.

Another distributed solution is proposed in [47]. which presents a distributed energy-saving management strategy for green cellular networks by using a message-passing framework. Distributed algorithms have low complexity, however, their weak point is, BSs do not aware of the other cells in these algorithms.

3.2 Network Planning Solutions

Optimum BS placement and planning can be used to optimize the network [48]. In [48], BSs are located based on traffic prediction. UEs (User Equipments) are sorted descending according to their data rate requirement, if there is an operational BS that can provide the data rate of the first UE in the list, this UE is connected to this BS and UE is removed from the list, otherwise, a new BS is turned on. This algorithm is run multiple times, all possible scenarios are investigated and best places for the BSs are determined.

Xiangnan Weng *et al.* [49] consider energy saving in cellular network planning stage. They investigate cell-zooming sufficiency and decide whether or not zooming existing cells is adequate for power consumption minimization. They suggest that after a point, cell-zooming is insufficient and smaller but more cells should be deployed. However, the tender spot of minimizing power consumption by optimizing network planning is, they cannot adapt the network in some special events where density of UEs is enormously large.

3.3 BS Sleep Mode Solutions

Georgios Kyriazis *et al.* [1] improved [48]. First they determine the location of BSs by using the algorithm from [48], then they turn on or off BSs continuously with another algorithm.

A traffic-aware base station sleep mode strategy for both one-tier and two-tier cellular networks is presented in [50]. In one-tier scenario, the optimal energy efficiency demonstrated to be independent of user density. In two-tier heterogeneous networks, they proposed an iterative algorithm to solve BS density problem.

A sleep mode technique is proposed for small cells in [51]. BSs are set to either on, stand-by, sleep or off state and optimization is made while considering coverage probability and wake-up times of BSs. However, this process is applied to a single small cell, not to other BSs of other tiers.

Performance of heterogeneous networks with sleep strategy is evaluated in [52]. They suggest that outage probability is proportional to femto cell density in heterogeneous networks. Addition of femto BSs in the network reduces the outage probability and increases the chances of users stay in active region when macro BSs are turned on due to the network strategy.

Yichen Kang *et al.* [53], formulate the energy efficiency problem as an integer optimization problem and develops a user offloading algorithm for this problem. These BS sleep mode proposals only decide whether a BS should be on or off and on BSs are working with full power even if there are a few UEs in the environment.

3.4 Hybrid Solutions

Vinay Chamola *et al.* [54] and Po-Han Huang *et al.* [55] formulate the energy optimization problem as an integer programming problem and propose heuristic algorithms for user association, cell scaling, and base station sleep strategy to solve this problem.

3.4.1 Opponent

Finally, a dynamic cell zooming and BS sleep optimization algorithm is proposed for 5G dense heterogeneous networks in [5]. In this work, they first decide whether macro and pico base stations are on or off, then, calculate the traffic between macro BSs, pico BSs, and UEs.

They formulated the problem as a linear programming problem, define some constraints and solve the problem with IBM CPLEX Mixed Integer Optimizer [56].

The constraints that they have defined are as follows where M represents the set of macro BSs, S represents the set of pico BSs and U represents the set of UEs:

- For each pair of endpoints that can communicate the amount of transmitted data rate must not exceed the link capacity:

$$x(e_1,e_2) \leq c(e_1,e_2)W_z, \qquad e1 \in M \cup S, e2 \in U. \tag{3.1}$$

  where $x(e_1,e_2)$ denotes the bandwidth allocated to e_2, $c(e_1,e_2)$ represents the spectral efficiency between nodes $e1$ and $e2$ and W_z denotes total bandwidth of e_1.

- No node can associate with the one in off state:

$$k(e_1,e_2) \leq y_{e_1}, \qquad e1 \in M \cup S, e2 \in U. \tag{3.2}$$

  where $k(e_1,e_2)$ is a binary variable representing the association between nodes $e1$ and $e2$ and y_{e_1} represents whether BS e_1 is on or off.

- Data can be received only from the associated node:

$$x(e_1,e_2) \leq k(e_1,e_2)c(e_1,e_2)W_z, \qquad e1 \in M \cup S, e2 \in U. \tag{3.3}$$

- Each user should be associated with only one node:

$$\sum_{m \in M} k(m,u) + \sum_{s \in S} k(s,u) \qquad u \in U. \tag{3.4}$$

Based on these constraints, they formulated the problem as

$$min \sum_{m \in M} y_m P_0(m) + \delta_m y_{zoom_m} P_m^{max} + \sum_{s \in S} y_s P_0(s) + \delta_s y_{zoom_s} P_s^{max}, \tag{3.5}$$

where P_0 is the minimum power consumption when the node is in idle mode, δ denotes the power amplifier efficiency of the infrastructure node, y_{zoom} is a variable between 0 and 1 to dynamically control BSs transmission power based upon the power requirements of the farthest user in the cell and P^{max} is the maximum RF output power of an infrastructure node.

We compare our results with the basic model and the model presented in [5]. In the basic model, all of the base stations are always active and transmit signals with the highest possible power levels. We employ the basic model to determine the overall gains. In [5], authors provide a similar power optimization algorithm however, they do not consider the outage probability and received *SINR* threshold of UEs.

CHAPTER 4

JOINT OPTIMIZATION OF CELL ZOOMING, SCHEDULING AND USER ASSOCIATION

In this chapter, the architecture of the network that our joint optimization of cell zooming, base station scheduling and user association algorithm (JOCell) is applied is described, the problem and constraints are defined formally and its complexity is presented.

4.1 Network Architecture

We consider an environment as shown in Figure 4.1 in which unnecessary BSs will be turned off and all active BSs do not have to work on full power. We assume that there are M BSs indexed by $i = 1, 2, ..., M$ and N UEs indexed by $j = 1, 2, ..., N$. The set of M base stations are connected to a mobile edge computing (MEC) entity. In this work, we formulate the joint sleep scheduling and cell zooming problem. The solution will be run by the MEC and the configuration of the network will be changed dynamically on the run.

In this architecture, BSs are directly connected to the MEC entity and MEC entities are connected to the GSM operator server. This entity determines which BSs should be active, UE-BS associations and transmit power of BSs and dynamically programmes the BSs according to these outcomes. To calculate these, MEC entity should know the distances between BSs and UEs and data rate requirements of UEs. Distance between a BS and a UE can be calculated with a feedback mechanism. UEs can send their received power back to the BS, and BS can send it to MEC. Because

MEC knows both BS transmit power and received power of UE, it can calculate the distance by using 4.8. Because MEC is connected to the server of the GSM operator, it can also detect the approximate data rate requirement of a user by analyzing the data rate demand of that user for the last 30 days.

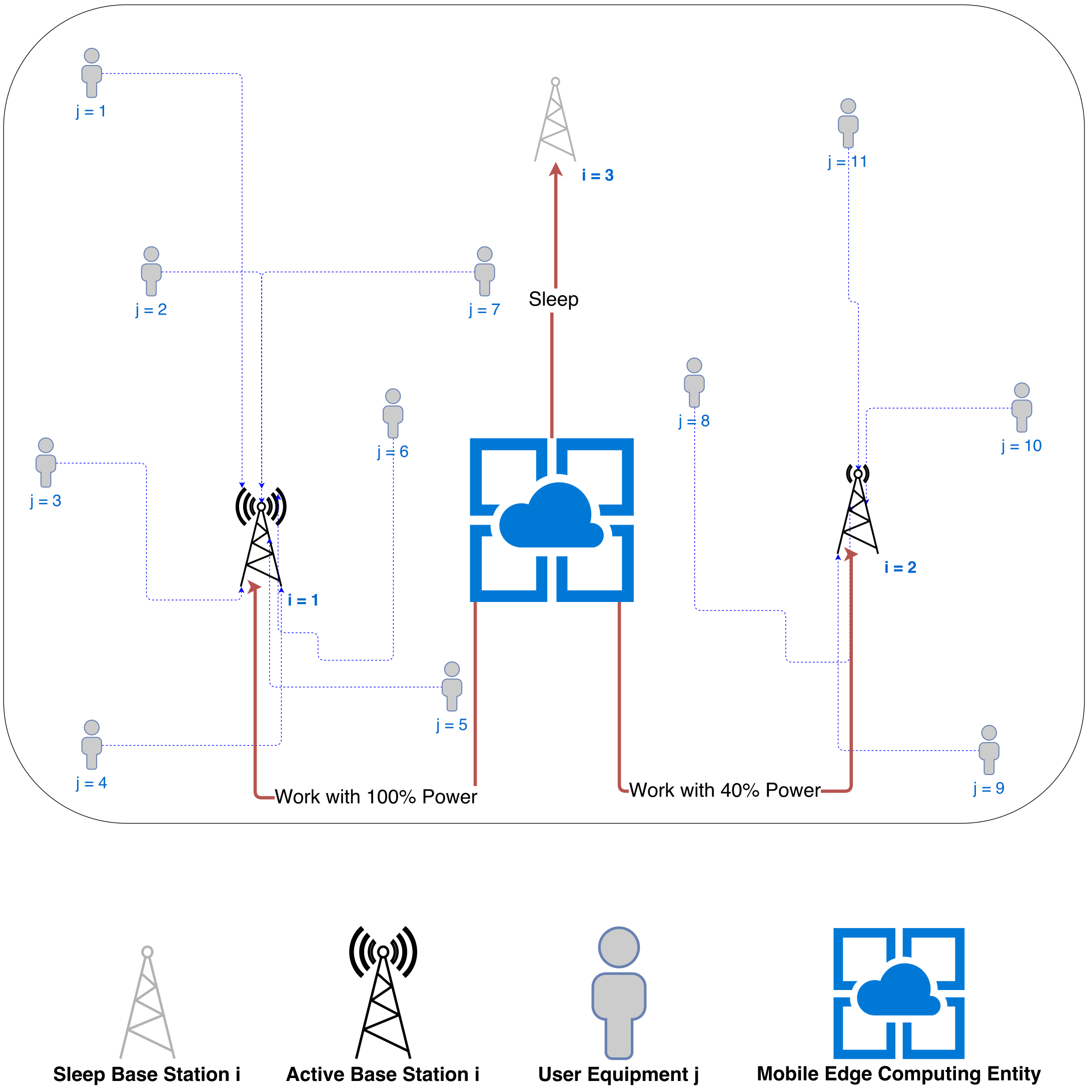

Figure 4.1: The mobile network topology considered in problem formulation.

4.2 List of Symbols

The symbols that are used in formal problem definition and their descriptions are listed in Table 4.1.

Table4.1: List of Symbols

Symbol	Description
a	UE-BS Association
o	BS Operation Mode
e	Efficiency
$SINR$	Signal-to-Interference-plus-Noise Ratio
r	UE rate requirement
w	Required Bandwidth
P_0	Idle BS Power Consumption
δ	Power Amplifier Efficiency
P^{out}	Full-load BS Power Consumption
L	Utilized Fraction of Bandwidth
W	Total Bandwidth of BS
$\mathscr{P}_O$	Outage Probability
$\mathscr{P}_O^*$	Outage Probability Threshold
C	Attenuation Factor
d	Distance
dr	User Data Rate Requirement
γ	Path-Loss Exponent
$\widehat{\lambda}$	BS Density
A	Area
T_S	$SINR$ Threshold

4.3 JOCell

The (spectral) efficiency between BS i and UE j, e_{ij}, is:

$$e_{ij} = log_2(1 + SINR_{ij}) \quad \text{bits/Hz} \tag{4.1}$$

where $SINR_{ij}$ denotes the received signal-interference-plus-noise ratio at UE j. For each user equipment j that is connected to base station i, the rate required by UE j is defined as r_{ij} Mbps. Therefore the required bandwidth, w_{ij}, is:

$$w_{ij} = \frac{r_{ij}}{e_{ij}} \quad \text{Mbps} \tag{4.2}$$

In order to represent the association between BS i and UE j, a binary variable "a_{ij}" can be defined as follows:

$$a_{ij} = \begin{cases} 1 & \text{if UE } j \text{ is connected to BS } i, \\ 0 & \text{otherwise,} \end{cases} \tag{4.3}$$

According to [57], the relation between power consumption P_c by a base station and the output power P_{out} is:

$$P_{consumed} = P_0 + \delta_i P_i^{out} \quad \text{W} \qquad\qquad P_{t_{min}} < P_i^{out} \leq P_i^{max}, \tag{4.4}$$

where P_0 is the minimum power consumption when the BS is in idle mode, δ_i denotes the power amplifier efficiency of a base station i which is the ratio of the total RF output power to total RF DC input [58], $P_{t_{min}}$ is the minimum transmit power of base stations and P_i^{max} is the maximum RF output power of an base station i at full load.

If the fraction of bandwidth to be utilized at BS i is defined as L_i, the output power of base station i becomes:

$$P_i^{out} = L_i P_i^{max} \quad \text{W} \tag{4.5}$$

where $0 \leq L_i \leq 1$ can be stated as [5]

$$L_i = \sum_{j \in U} a_{ij} \frac{w_{ij}}{W_i} \tag{4.6}$$

when the total bandwidth allocated to BS i is W_i.

To maintain the QoS in the network, the outage probability $\mathscr{P}_O$ has to be always below than a threshold $\mathscr{P}_O^*$:

$$\mathscr{P}_O \leq \mathscr{P}_O^*. \tag{4.7}$$

If we assume that base stations are randomly deployed in a cellular network, the received power of a uniform randomly selected point (UE) in the network from a base station considering simple path-loss model becomes

$$P_r = CP_t\left(\frac{d_0}{d}\right)^{\gamma}, \tag{4.8}$$

where C is the aggregated attenuation factor which is computed at the reference distance $d_0 = 1m$, P_t is transmit power, d is distance between the selected point and the associated base station, and γ is path-loss exponent. According to [59], this basic channel model is applicable for indoor scenarios like an office. Based on this model [60], the outage probability $\mathscr{P}_O$ is

$$\mathscr{P}_O = e^{-\pi\widehat{\lambda}(CP_t/T)^{2/\gamma}}, \tag{4.9}$$

where $\widehat{\lambda}$ is the base station density and T is the receiver sensitivity. We define $o_i = 1$ when BS i is on and active, it is zero otherwise. Let A represent the area. Then, the estimated density of the network, i.e., the ratio of the active BSs to the area, is

$$\widehat{\lambda} = \frac{\sum_{i\in S} o_i}{A}. \tag{4.10}$$

Consequently, the minimum required transmit power of a base station, $P_{t_{min}}$ calculated using (4.9) that satisfies $\mathscr{P}_O^*$ and sets the outage probability less than the threshold value is

$$P_{t_{min}} = \frac{T}{C}\left(\frac{-log(\mathscr{P}_O^*)}{\pi\widehat{\lambda}}\right)^{\gamma/2} \quad \text{W}. \tag{4.11}$$

4.4 Constraints

Moreover, there are some constraints in this system. If UE j is associated with BS i, then the allocated rate to the user r_{ij} must not exceed the capacity and also satisfy the data rate requirement R_j (Mbps) of that user; i.e.,

$$a_{ij}e_{ij}W_i \geqslant r_{ij} \geqslant R_j \tag{4.12}$$

Here, we assume that the user requirements are known in advance. UE j cannot associate with BS i that is off, $a_{ij} \leq o_i$ where $o_i \in \{0,1\}$ denotes whether the BS is OFF or ON respectively. User j can be associated with at most one BS at a time, i.e.,

$$\sum_{i=1}^{M} a_{ij} \leq 1 \tag{4.13}$$

UE j can only be associated with BS i when $SINR_{ij}$ is greater than the SINR threshold value, T_S,

$$a_{ij}SINR_{ij} \geq T_S \tag{4.14}$$

Finally, a UE should connect to the BS that provides the highest SINR value among other active BSs. That is,

$$SINR_{ij} \geq SINR_{kj} \tag{4.15}$$

where $i,k = 1,2,\ldots,M$ and $i \neq j$.

4.5 Objective

Based on the model and the constraints which are defined in the previous section, the objective of the optimization problem is to minimize the total power consumption in the network that can be expressed as

$$min\left(\sum_{i=1}^{M} o_i\left(P_0(i)+\delta_i\left(\sum_{j=1}^{N}\left(a_{ij}\frac{w_{ij}}{W_i}\right)\right)P_i^{max}\right)\right) \quad \text{W.} \tag{4.16}$$

4.6 Complexity

The solutions to this problem will yield o_i and a_{ij} values where

$$o=\begin{bmatrix} o_1 & o_2 & ... & o_M \end{bmatrix} \qquad\qquad o_i \in \{0,1\}$$

and

$$a=\begin{bmatrix} a_{1,1} & a_{1,2} & \cdots & a_{1,N} \\ a_{2,1} & a_{2,2} & \cdots & a_{2,N} \\ \vdots & \vdots & \ddots & \vdots \\ a_{M,1} & a_{M,2} & \cdots & a_{M,N} \end{bmatrix} \qquad\qquad a_{ij} \in \{0,1\},$$

respectively. o vector tells us which BS operational and on and a matrix which BS a user should connect.

The o vector consists of M elements and a matrix consists of MN elements. There are 2^M different solutions for $\boldsymbol{o}$ and 2^{MN} different solutions for $\boldsymbol{a}$. Therefore, the search space of this combinatorial optimization problem is

$$O(2^{MN+M})$$

This is a linear integer programming problem and search space grows exponentially with the increase in the number of BSs and UEs. For this reason, mobile edge computing should be used to run our algorithm to solve this problem, because if the algorithm is used in a centralized solution, the number of BSs and UEs would be very large and solving the problem in an eligible time would be impossible. Therefore, the network should be divided into small sections and our solution should me moved to the edges of these sections.

CHAPTER 5

RESULTS & DISCUSSION

5.1 Methodology

We implemented (4.16) in MATLAB Global Optimization Toolbox. We defined our objective minimization function and constraints in MATLAB and we employ genetic algorithm (GA) solver of MATLAB Global Optimization Toolbox to solve the optimization problem. The parameter values of this implementation, the genetic algorithm configuration that we used in the proposed algorithm, the parameters of particle swarm optimization algorithm, simulated annealing algorithm and pattern search polling algorithm that we used to compare with our algorithm are presented in Table 5.1, Table 5.2, Table 5.3, Table 5.4 and Table 5.5 respectively.

We present the power consumption results together with user satisfaction measure. In this work, the UE satisfaction (S) is calculated as follows:

$$S = \frac{\sum_{i \in S} \sum_{j \in U} a_{ij}}{N} \tag{5.1}$$

As one of our constraints, if a user is associated with a base station, then it means that the data rate requirement of that user is satisfied and the received $SINR$ value from associated BS is higher than the threshold value. Under these circumstances, a user gets associated with a base station when its QoS requirement is satisfied. Therefore, the ratio of the number of the users that are associated with a base station to the number of all users in the system gives us the user satisfaction ratio.

Table5.1: System Parameters

Parameter	Value	Unit	Reference
P_0	14.9	W	[5]
P^{max}	125	mW	[61]
Carrier Frequency	3.4	GHz	[61]
Bandwith	20	MHz	[61]
δ	8		[5]
Thermal Noise Level	-174	dBm/Hz	[61]
C	-30	dBm	[60]
T	-90.86	dBm	[60]
γ	1.69		[61]
A	250	m^2	
$\mathscr{P}_O^*$	0.02		
T_S	-18	dB	[62]

We run our simulations for an indoor scenario, like a shopping mall. We set the channel model and the system parameter values according to this scenario. The locations of BSs and UEs are uniform randomly selected and GA is run to determine the active BSs and the users connected to them.

Table5.2: Genetic Algorithm Parameters

Parameter	Value
$CrossoverFraction$	0.8
$MaxGenerations$	100 $\times M \times N$
$MaxStallGenerations$	50
$MaxStallTime$	∞
$MaxTime$	∞
$MigrationDirection$	Both
$MigrationFraction$	0.2
$MigrationInterval$	20
$FunctionTolerance$	10^{-6}
$ConstraintTolerance$	10^{-3}

Table5.3: Particle Swarm Optimization Algorithm Parameters

Parameter	Value
$FunctionTolerance$	10^{-6}
$MaxIterations$	$200 \times M \times N$
$MaxStallIterations$	$20 \times M \times N$
$MaxStallTime$	∞
$MaxTime$	∞
$SelfAdjustmentWeight$	1.49
$SocialAdjustmentWeight$	1.49
$SwarmSize$	$10 \times M \times N$

Table5.4: Simulated Annealing Algorithm Parameters

Parameter	Value
$FunctionTolerance$	10^{-6}
$InitialTemperature$	100
$MaxFunctionEvaluations$	$3000 \times M \times N$
$MaxIterations$	∞
$MaxStallIterations$	$500 \times M \times N$
$MaxTime$	∞
$ReannealInterval$	100

Table5.5: Pattern Search Polling Algorithm Parameters

Parameter	Value
$FunctionTolerance$	10^{-6}
$ConstraintTolerance$	10^{-6}
$InitialMeshSize$	1
$MaxFunctionEvaluations$	$2000 \times M \times N$
$MaxIterations$	$100 \times M \times N$
$MaxMeshSize$	∞
$MaxTime$	∞
$MeshContractionFactor$	0.5
$MeshExpansionFactor$	2
$MeshTolerance$	10^{-6}
$StepTolerance$	10^{-6}

5.2 Results of the Proposed Algorithm

In our simulation scenario, 1, 3, 5, 8, 10, 15, 20, 30, 40 and 50 UEs have been uniform randomly distributed in an environment that has 1, 3, 5, 8 and 10 base stations. Power consumption values for different UE densities in the area and for different BS densities in the area are shown in Figure 5.1.

As it can be seen in Figure 5.1, only 1 BS out of 10 is active (in on-state) when the number of UEs is fewer than 15 in the network, the power consumption value will be around 15 W. The reason behind that is, even if there are 10 BSs in the environment, when number of active UEs are below 15, only 1 BS is needed to be activated to satisfy the QoS requirements like (4.9) and (4.15) in the network. Similarly, additional BSs have to be activated to satisfy UEs in the system as more and more UEs join the network and this causes an increase in the amount of consumed power. For instance, as it is shown in Figure 5.1, the average active BSs is 2.62 for 20 UEs, 4.16 for 30 UEs, 5.82 for 40 UEs and 7.17 for 50 UEs and the average power consumption values are 40.5, 64.1, 89.4 and 110.3 W, respectively.

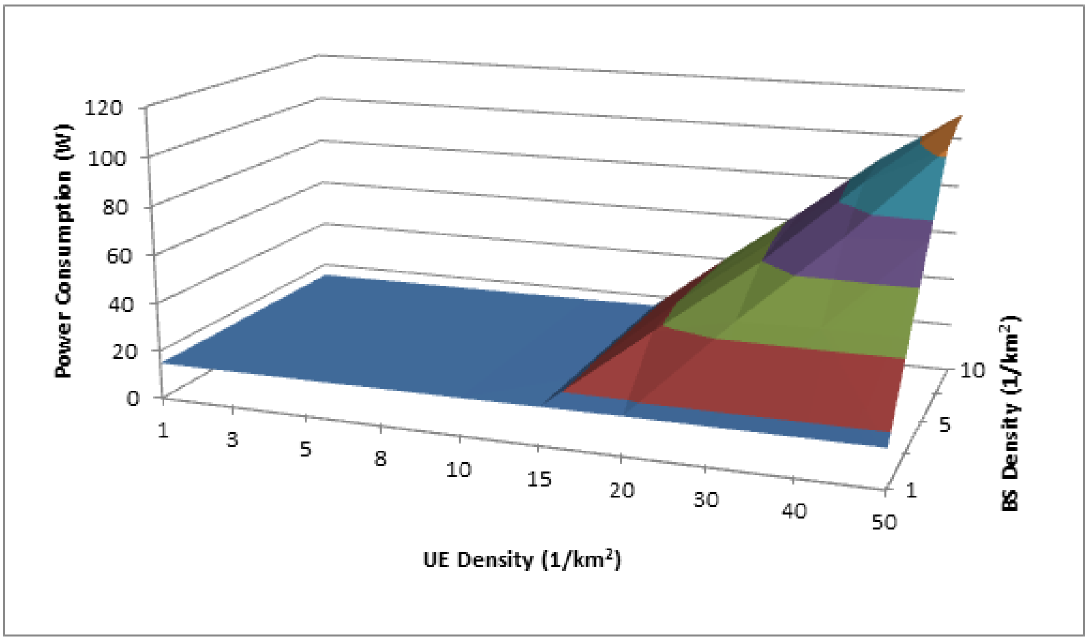

Figure 5.1: Power consumption values for UE and BS densities.

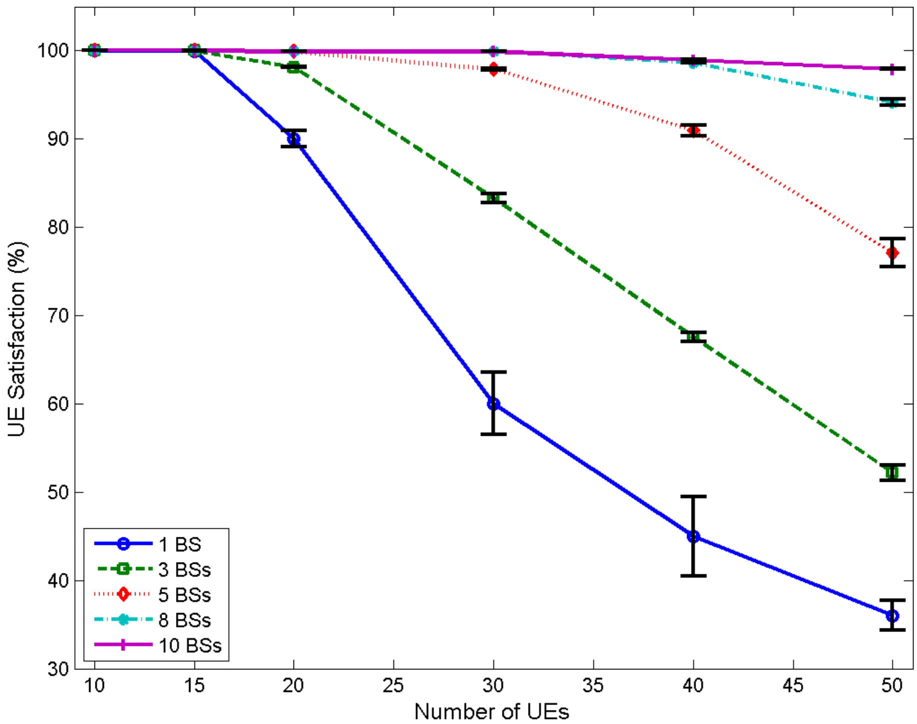

Figure 5.2: UE satisfaction percentage values for 1, 3, 5, 8 and 10 BSs.

In Figure 5.2, UE satisfaction percentage values for different BS and UE numbers are visualized. This figure points out that as the number of UEs increases, overall UE satisfaction percentage decreases and new BSs are needed to be activated.

5.3 Comparison with the Opponent

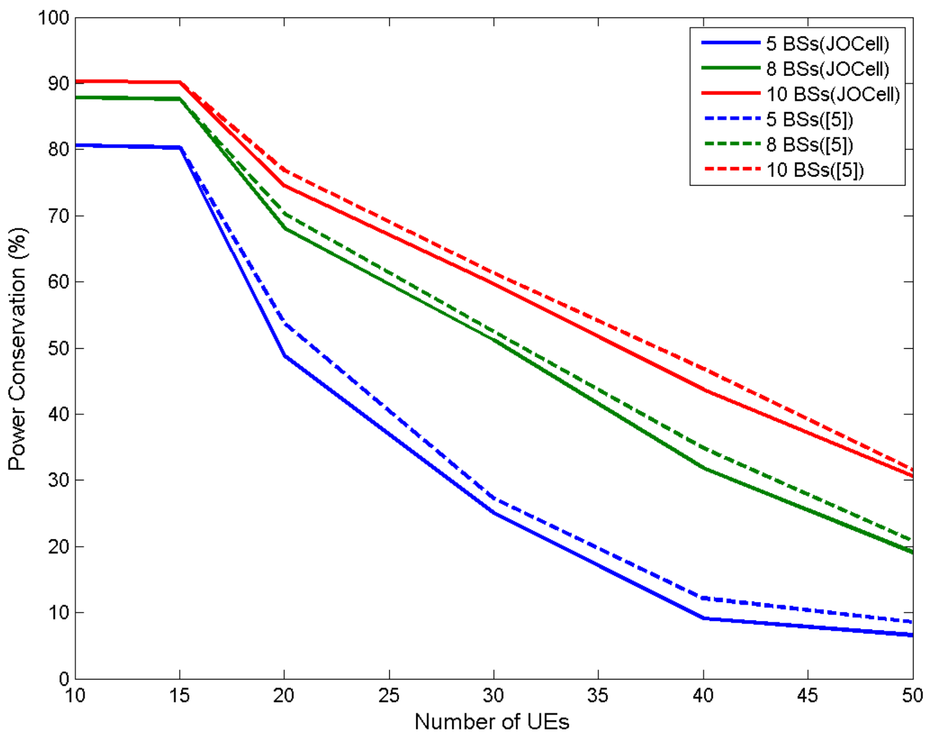

Figure 5.3: Power conservation percentage values for 5, 8 and 10 BSs.

In the basic model, the overall energy consumption in the network will not be affected by UEs density since all BSs are always on and work with their maximum transmit power. We compare the amount of power conservation and the average percentage of active BSs of the proposed algorithm with the proposal in [5] in Figure 5.3 and Figure 5.4 respectively. In [5], authors provide a power optimization algorithm however, they did not consider the outage probability and any constraint for choosing the best BSs candidate for each UEs. Although, [5] can conserve for about 5% more power respect to JOCell, but, this is achieved by sacrificing QoS and reducing UE satisfaction dramatically by ignoring some vital constraints such as (4.9) and (4.15).

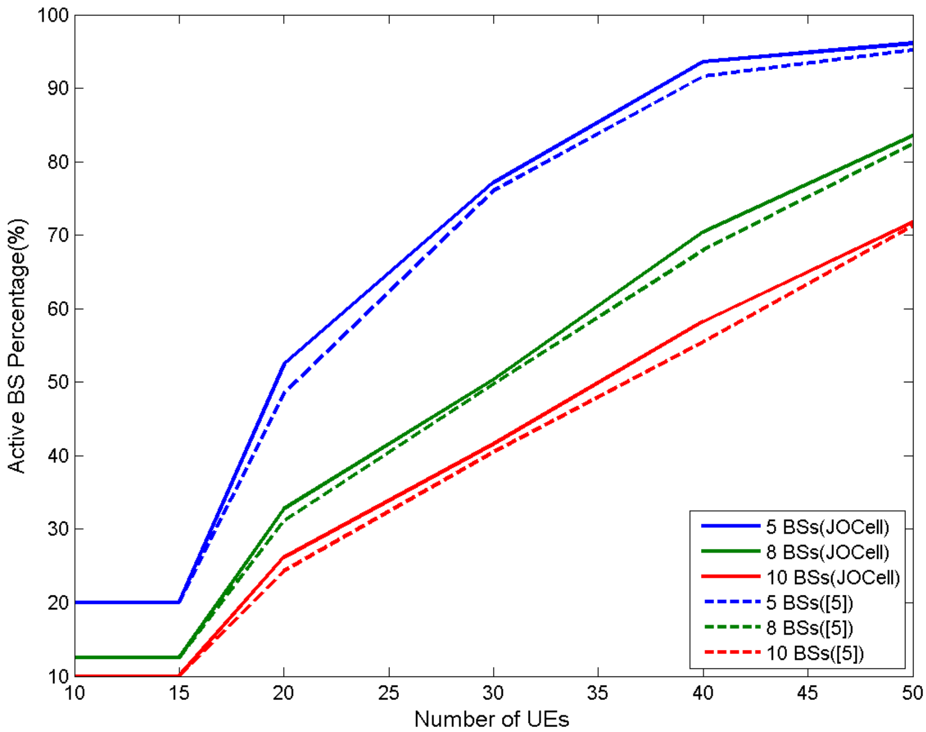

Figure 5.4: Active BSs percentage.

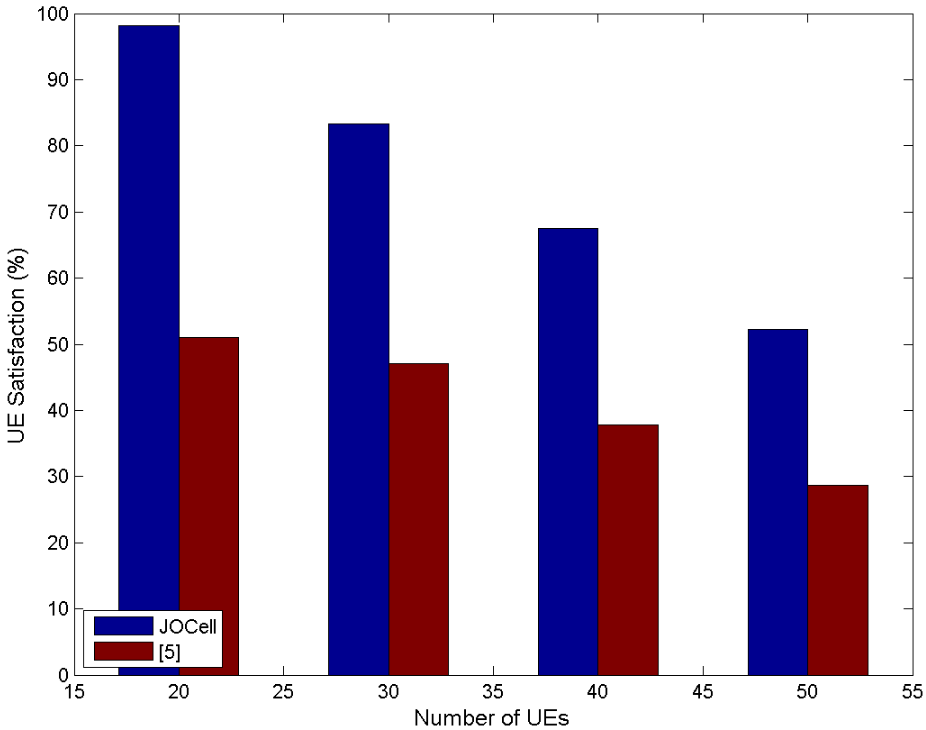

Figure 5.5: UE satisfaction percentage values for JOCell and [5] for 3 BSs.

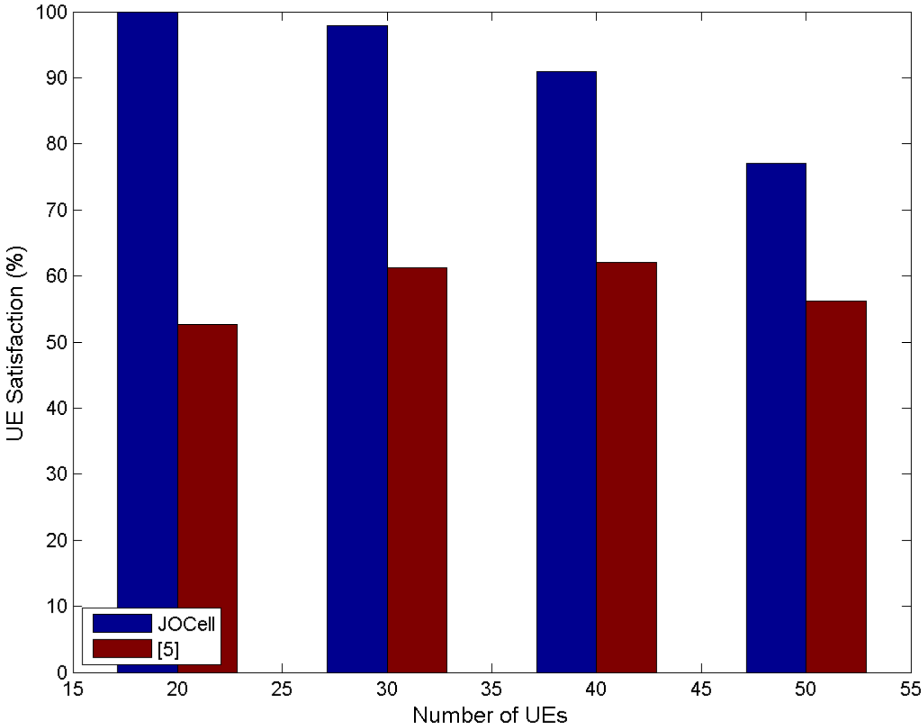

Figure 5.6: UE satisfaction percentage values for JOCell and [5] for 5 BSs.

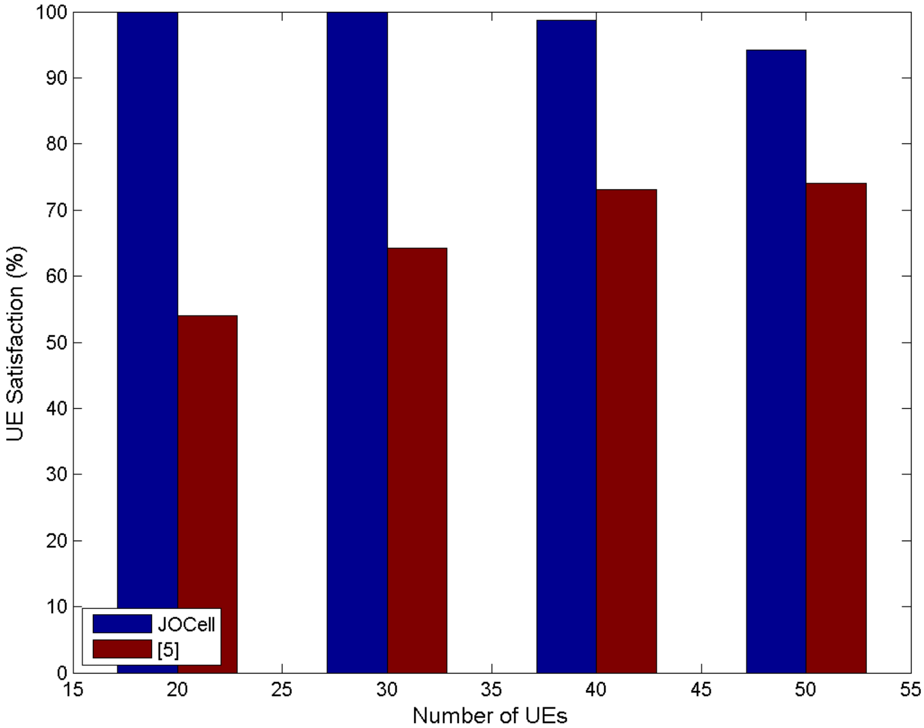

Figure 5.7: UE satisfaction percentage values for JOCell and [5] for 8 BSs.

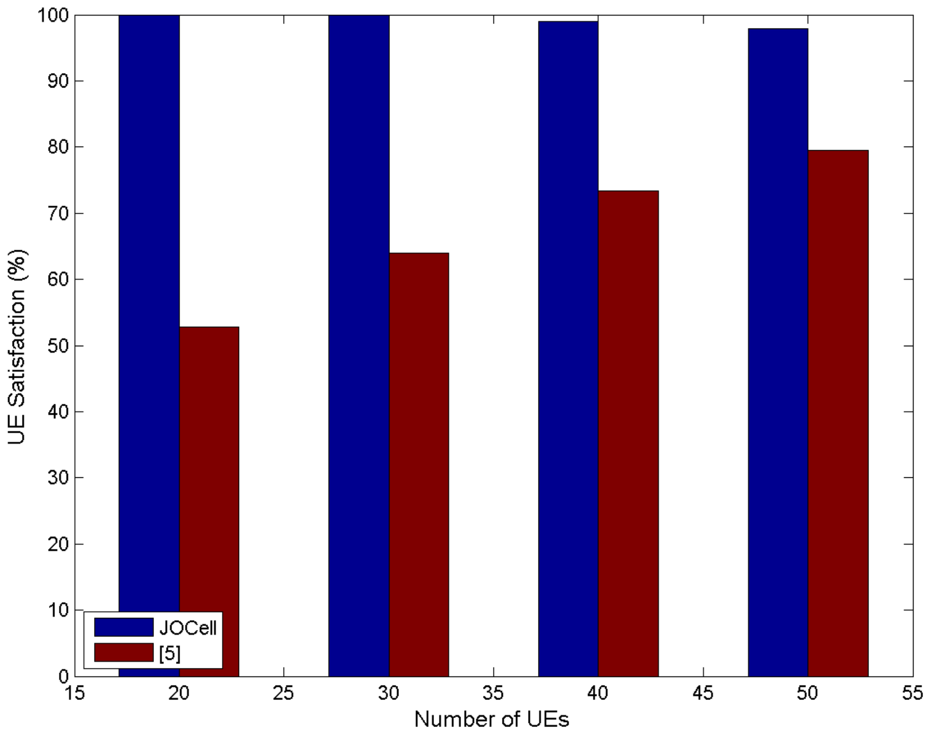

Figure 5.8: UE satisfaction percentage values for JOCell and [5] for 10 BSs.

In Figure 5.5, Figure 5.6, Figure 5.7 and Figure 5.8, we compare the UE satisfaction in the proposed algorithm with [5] for 3, 5, 8 and 10 respectively.

In these figures, we compare the UE satisfaction in the proposed algorithm with [5] for 3, 5, 8 and 10 BSs respectively. As it is shown, in all of these cases, due to our QoS constraints like (4.9) and (4.15), our proposed algorithm can satisfy more UEs in comparison with [5]. In general, we improved the user satisfaction in comparison with [5] up to 47%.

In Figure 5.4, ratio of On BSs to all BSs is shown for both our algorithm and [5]. It can be observed that values of [5] are up to 7% better than our values, because, in [5], QoS of the network is sacrificed by reducing the number of active BSs to save more energy, while in the proposed algorithm, we need to turn on more BS to maintain UE satisfaction in the network.

Moreover, if we investigate Figure 5.2 and Figure 5.4 together; we can see that unnecessary BSs are not turned on. If active BS percentage is below 100%, then UE satisfaction percentage is near to 100%. In other words, if our algorithm decides that some of the base stations are enough to satisfy all UEs, then it does not turn on the other BSs, otherwise, it activates another BS. Therefore, inactive BSs in the system means that they are not needed because the remaining BSs are enough.

5.4 Impacts of System Parameters to Our Solution

Besides the comparison of the results of JOCell with the results of [5] and the traditional model; we also have observed the impacts of different system parameter values over the power consumption and UE satisfaction values of our solution.

In order to show the impacts of the parameters, in each case, we only change one parameter and keep the other parameters constant and get the results for three different scenarios; sparse scenario which has 5 BSs and 15 UEs, normal scenario which has 5 BSs and 30 UEs and dense scenario which has 5 BSs and 50 UEs.

The first system parameter of which we observed the impacts on power consumption and UE satisfaction is user data rate requirement, R_j. We have run the simulation for different user data rate requirement values like 10 Mbps, 15 Mbps, 20 Mbps, 30 Mbps and 40 Mbps. When the requirement value increases; Figure 5.9 shows that the power consumption value increases; and Figure 5.10 shows that, UE satisfaction percentage decreases. The reason behind it is, increasing the user requirement means increasing the need of a user, therefore with increasing user data rate, UE satisfaction decreases and because new BSs are activated more easily, power consumption increases.

We have got the simulation results for different carrier frequency values like 1.0 GHz, 2.0 GHz, 3.4 GHz, 4.0 GHz and 4.5 GHz. When the carrier frequency value increases; as the Figure 5.11 illustrates, power consumption decreases; and as the Figure 5.12 depicts, UE satisfaction percentage increases. This is because, increasing the carrier frequency means increasing the capacity of BSs, therefore with increasing carrier frequency, UE satisfaction increases and because less BSs become enough to satisfy the users, power consumption decreases.

We tried different path-loss exponent values like 1.69, 2.00, 3.00, 4.00 and 5.00 and

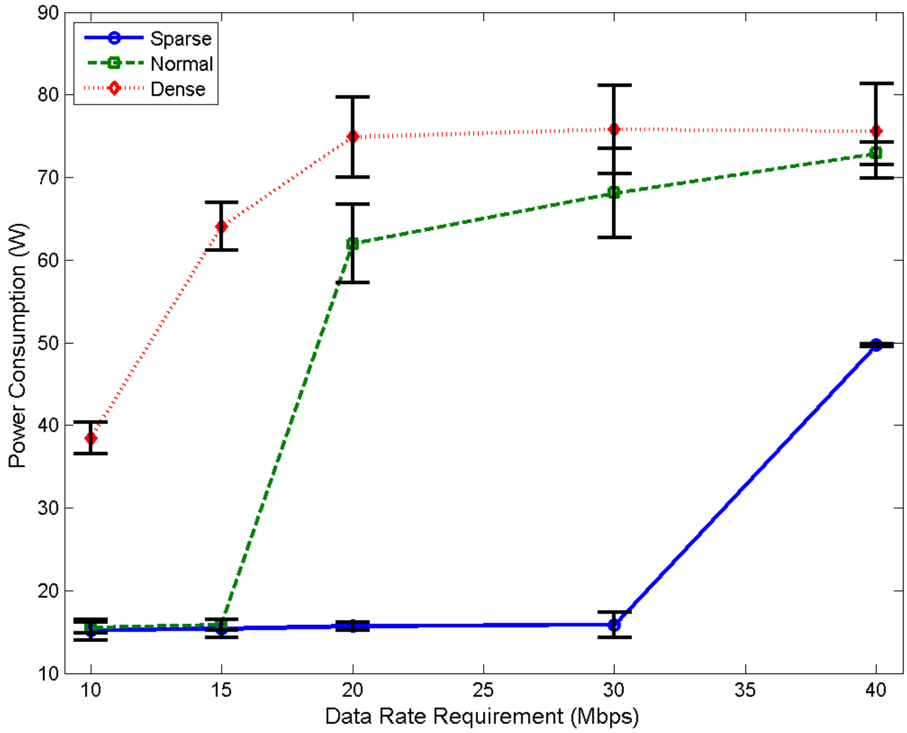

Figure 5.9: User data rate requirement effects on power consumption.

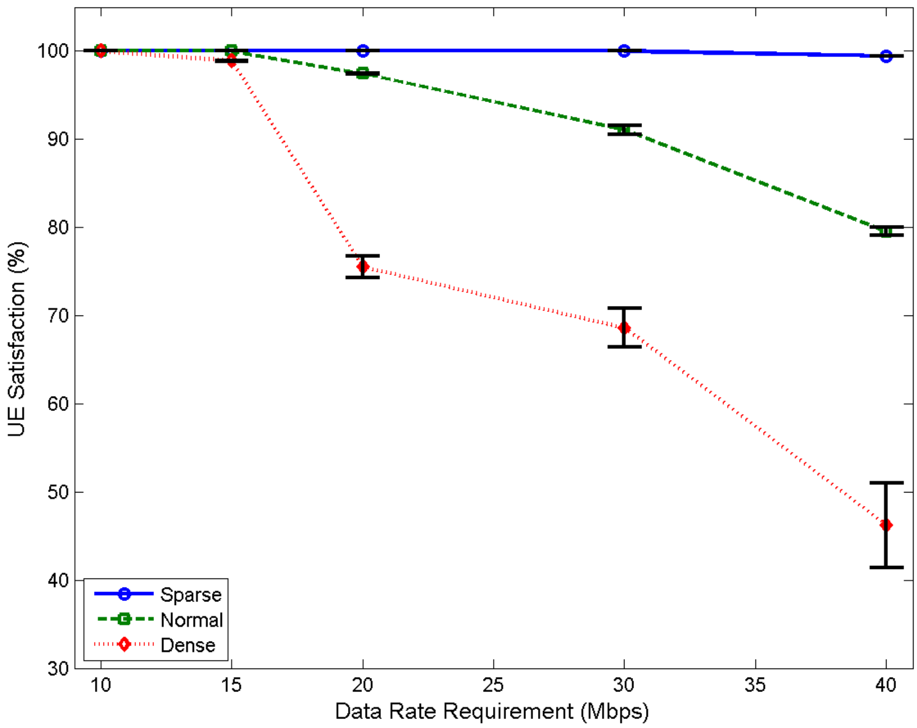

Figure 5.10: User data rate requirement effects on UE satisfaction percentage.

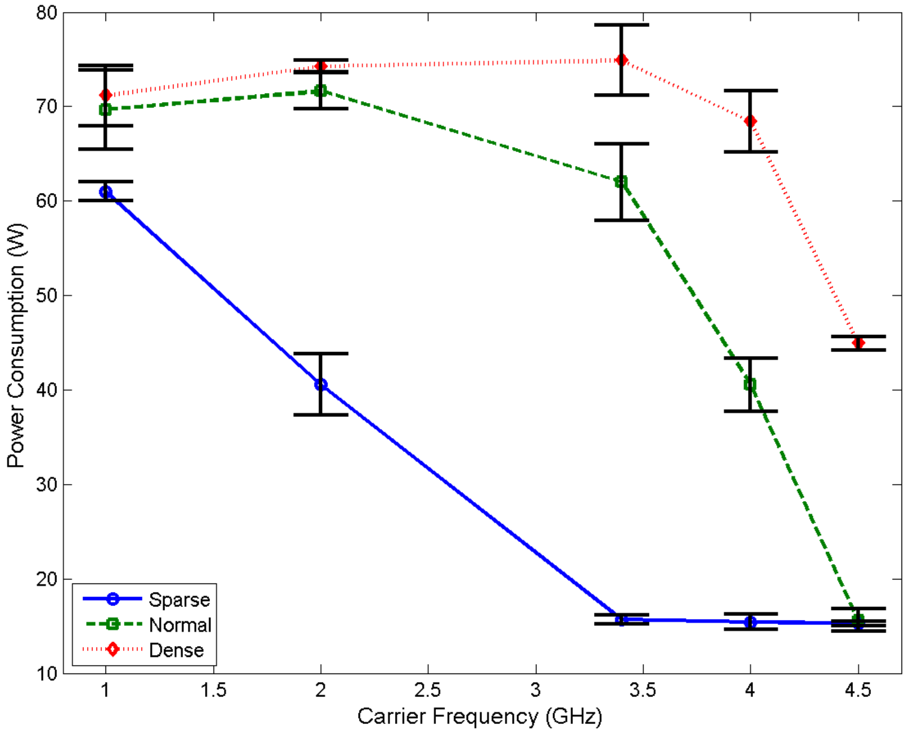

Figure 5.11: Carrier frequency effects on power consumption.

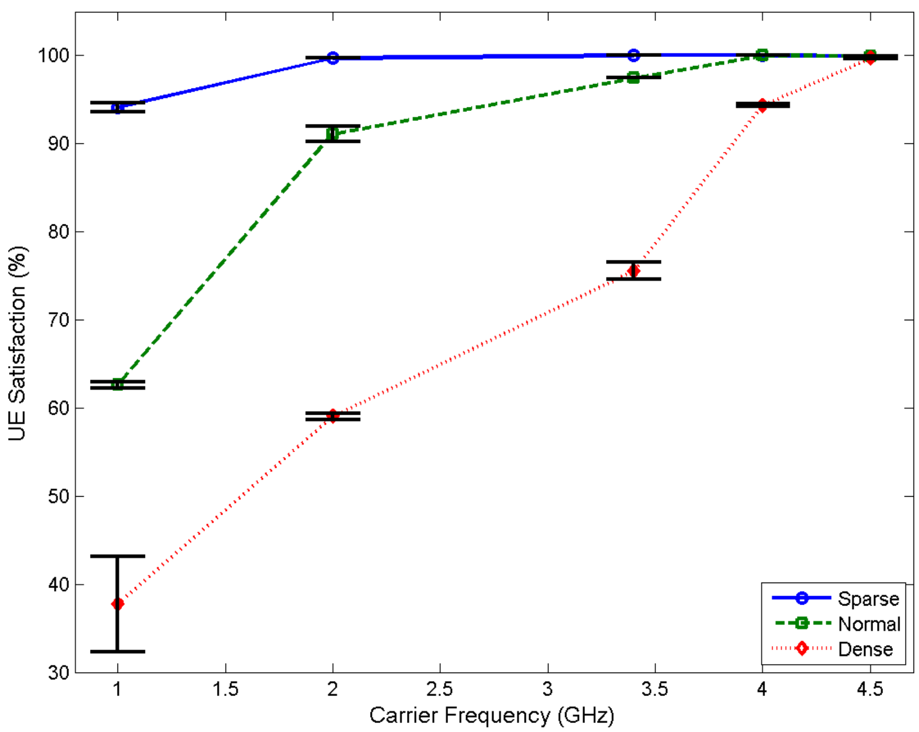

Figure 5.12: Carrier frequency effects on UE satisfaction percentage.

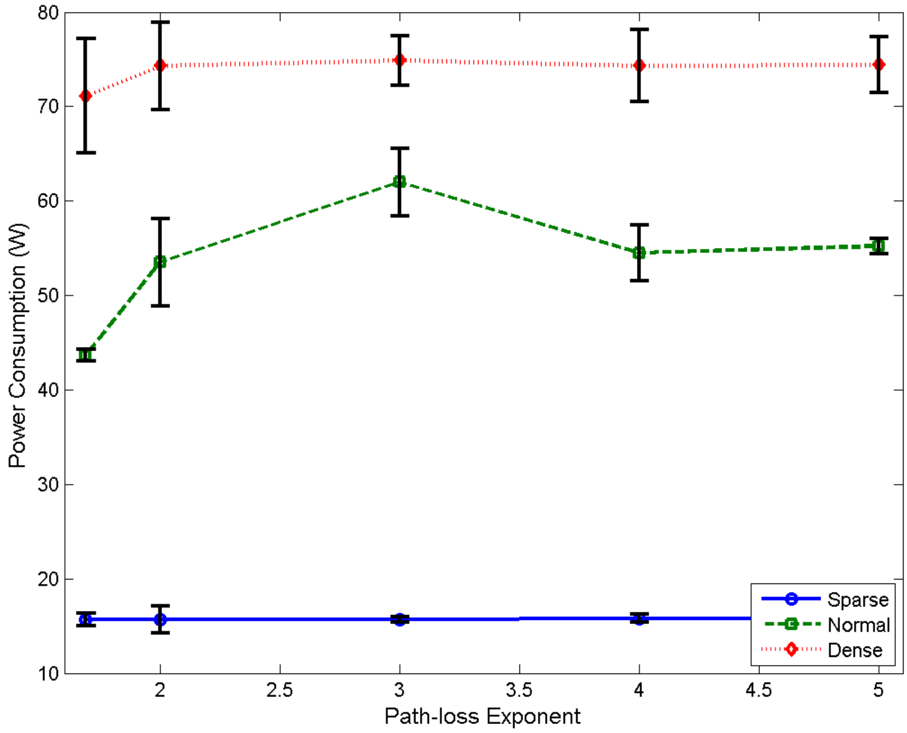

Figure 5.13: Path-loss exponent effects on power consumption.

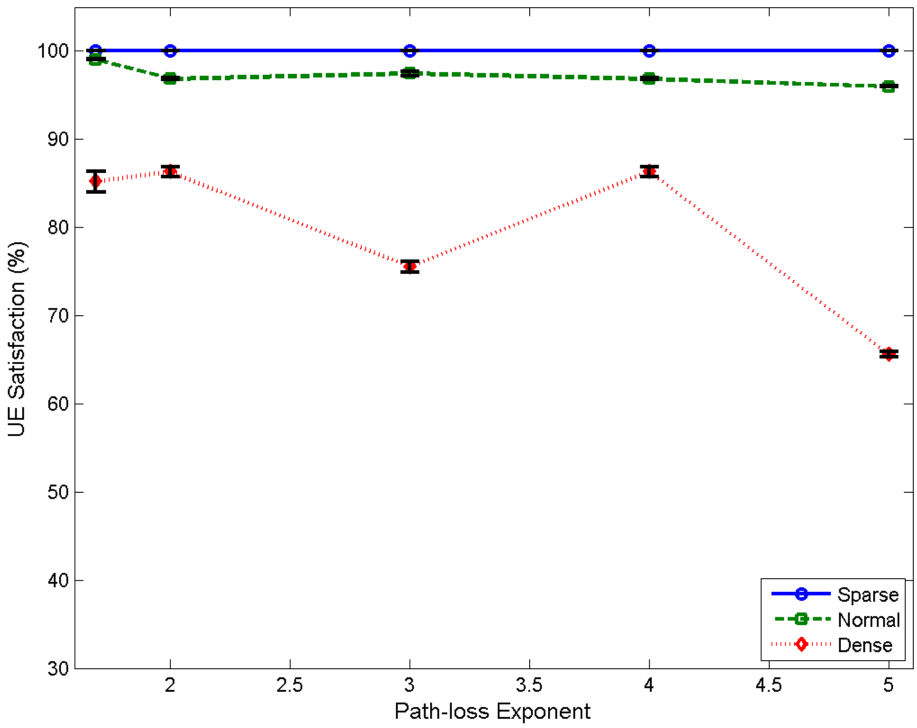

Figure 5.14: Path-loss exponent effects on UE satisfaction percentage.

got the power consumption and UE satisfaction percentage values. Different environments have different path-loss exponent values. The value varies from 1.6 to 1.8 for indoor, 2.7 to 3.5 for urban area, 3 to 5 for suburban area and equal to 2 for free space [63]. When the path-loss exponent value decreases; as Figure 5.13 shows, power consumption decreases; and as can be understood from Figure 5.12, UE satisfaction percentage increases. (4.9) shows that path-loss exponent directly affects the outage probability, increasing path-loss exponent means increasing outage probability, therefore UE satisfaction percentage increases when path loss exponent decreases. Moreover, (4.11) shows that path-loss exponent affects the minimum transmit power of base stations, therefore power consumption value decreases when path-loss exponent decreases.

5.5 MATLAB Meta-Heuristic Functions

In this section, we examined four different meta-heuristic functions of MATLAB Global Optimization Toolbox, which are:

- **GA:** Genetic Algorithm
- **PS:** Pattern Search Polling Algorithm
- **SO:** Particle Swarm Optimization Algorithm
- **SA:** Simulated Annealing Algorithm

We observed the impact of some parameters to these algorithms in order to choose the optimum parameter values of each algorithm. Moreover, we implemented our solution with these algorithms and compare the resulting power consumption and running time values to decide which algorithm is the most suitable for our solution.

5.5.1 Impacts of Genetic Algorithm Parameters

In addition to the system parameters, we also observed the impacts of different genetic algorithm parameters over the proposed optimization model.

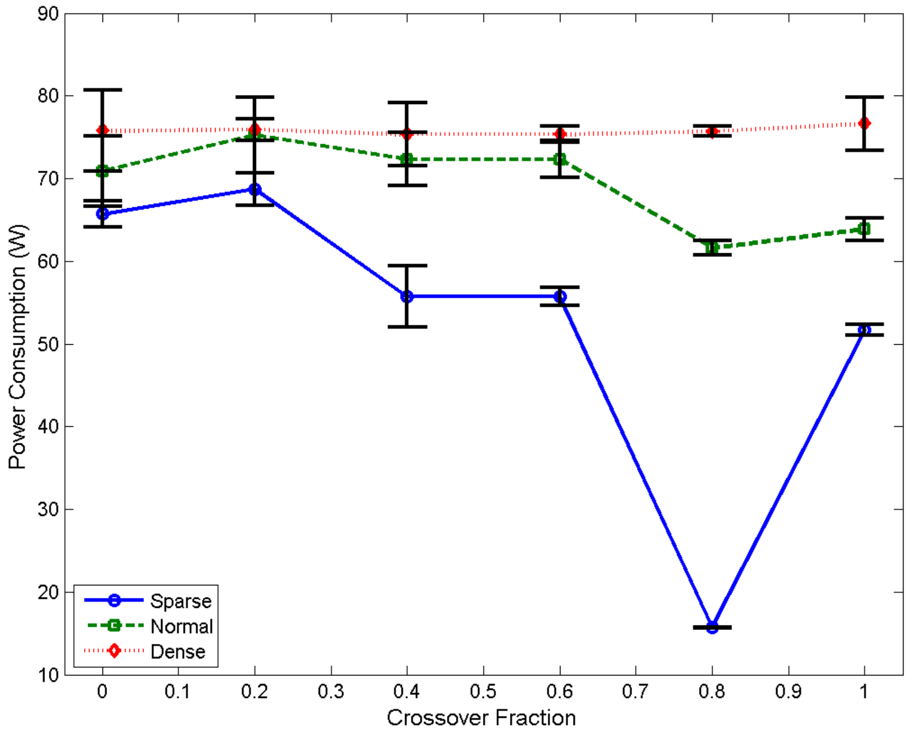

Figure 5.15: Crossover fraction effects on power consumption.

We run the simulation for different crossover fraction values like 0, 0.2, 0.4, 0.6, 0.8 and 1.0. 0 as crossover fraction value means that there is no crossover in the system, just mutation; and 1.0 as crossover fraction value means the opposite, the next generation is decided only with crossover. Figure 5.15 proves that the best value is 0.8. From 0 to 0.8, power consumption decreases while crossover fraction increases. However, after 0.8 to 1.0 power consumption value again starts to increase. Both mutation and crossover are vital for genetic algorithm. using one of them and ignoring the other does not generate good results as shown in Figure 5.15. However, in Figure 5.15, the trials show that 0.8 is the optimum fraction value for the crossover.

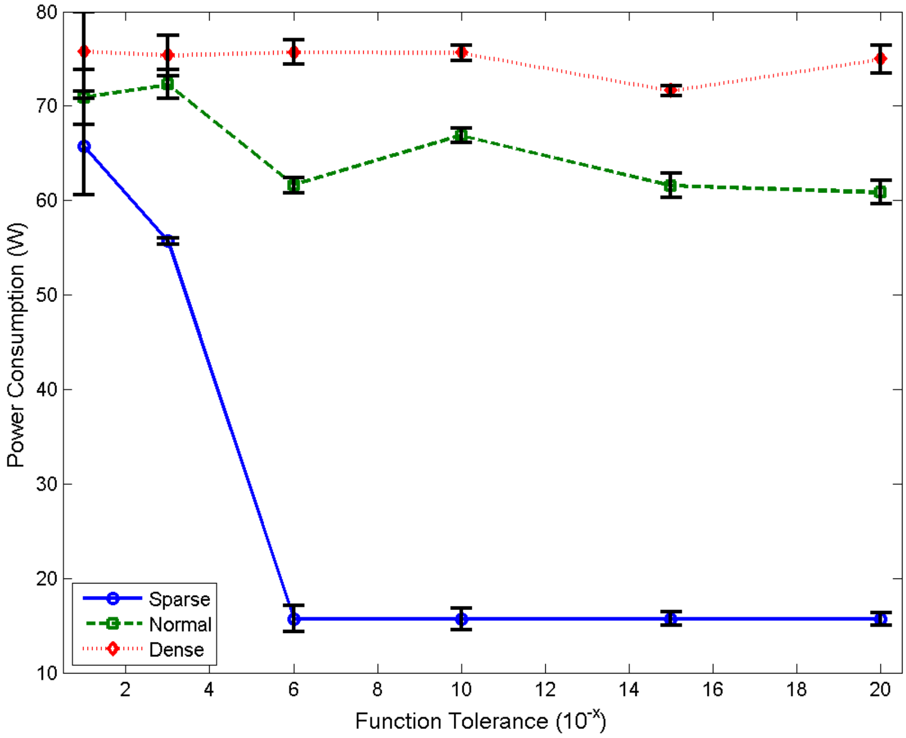

Figure 5.16: Function tolerance effects on power consumption.

We tried different function tolerance values like 10^{-1}, 10^{-3}, 10^{-6}, 10^{-10}, 10^{-15} and 10^{-20} and got the power consumption values. The algorithm stops if the average relative change in the best fitness function value over the generations is less than or equal to function tolerance. When the function tolerance value decreases; as can be seen from Figure 5.16, power consumption decreases until 10^{-6} and after that does not change much. It is because 10^{-6} is enough for the algorithm. Less than 10^{-6} is unnecessary over-precision. More than that value causes premature termination of the algorithm. Therefore, 10^{-6} is the optimum function tolerance value.

The last parameter of genetic algorithm we examined is maximum generation. For maximum generation, we set the number of base stations to 5 and the number of users to 15. We have tried different maximum generation values like 750, 1875, 3750, 5625, 7500, 11250 and 15000.

Figure 5.18 shows that running time increases with the maximum generation value. However, as Figure 5.17 illustrates, after 7500 maximum iterations, increasing max-

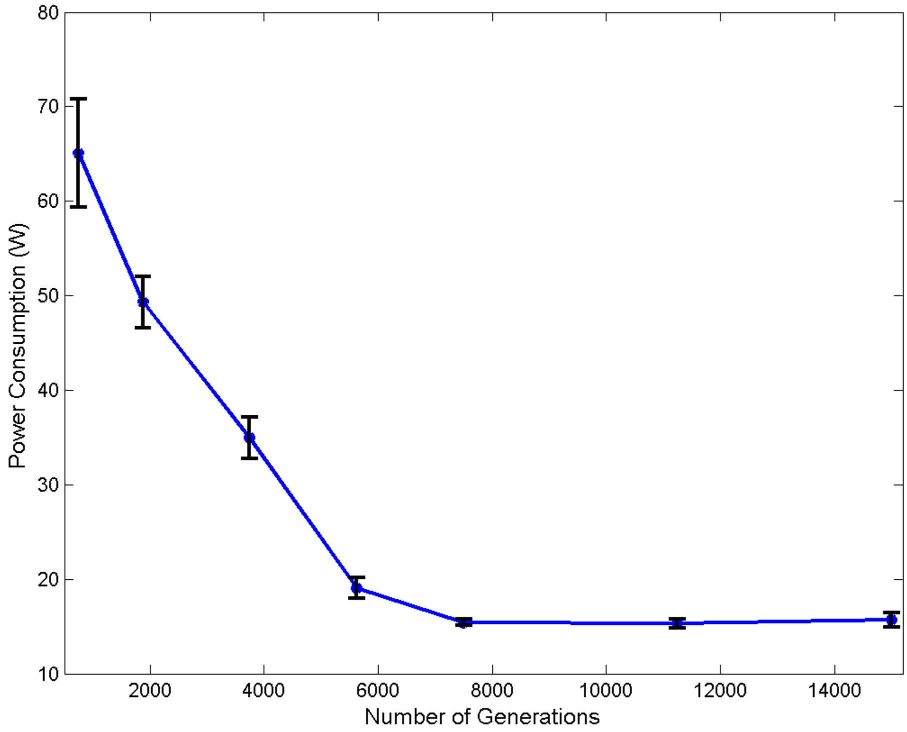

Figure 5.17: Power consumption values for different maximum generation values.

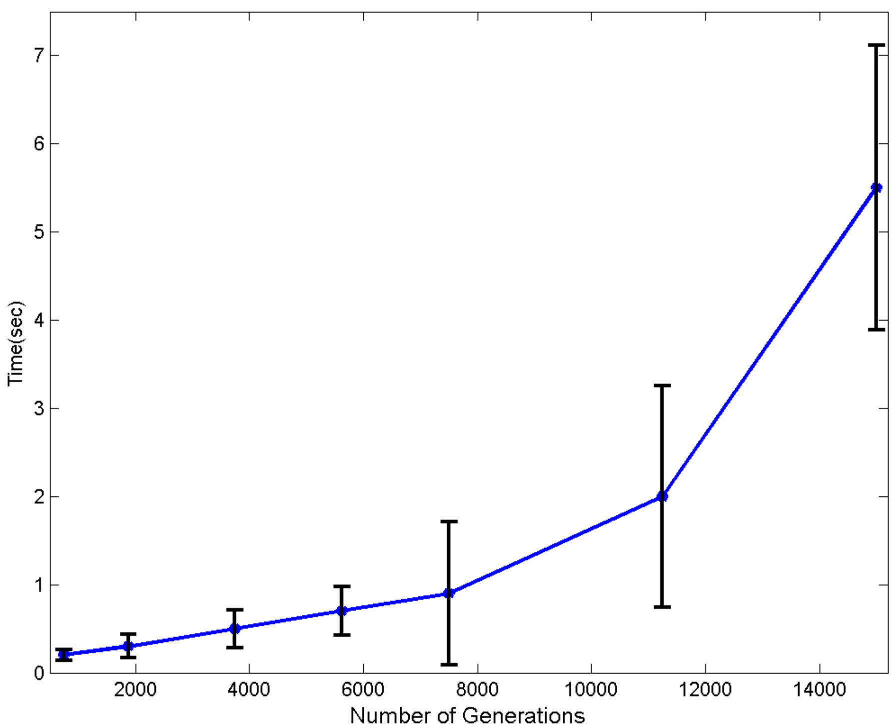

Figure 5.18: Running time values for different maximum generation values.

imum generation value does not have an effect on the power consumption value. Therefore, the optimum value for maximum generations to reach the required result is 7500, which is $100 \times M \times N$ for this case.

5.5.2 Impacts of Particle Swarm Optimization Parameters

We observed the impacts of different particle swarm optimization algorithm parameters over the proposed optimization model.

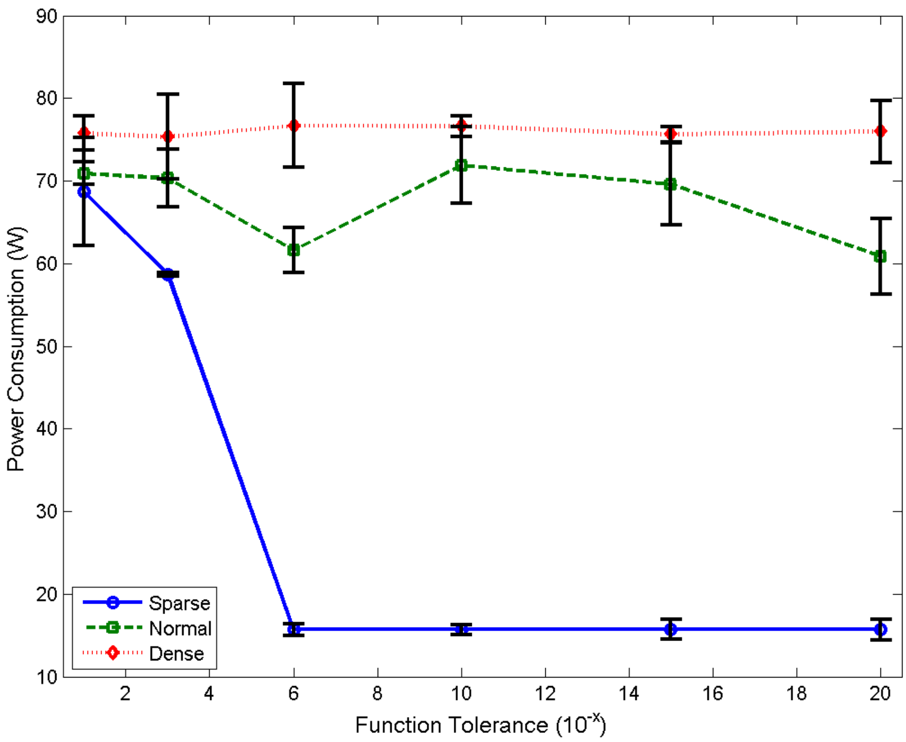

Figure 5.19: Function tolerance effects on power consumption.

We tried different function tolerance values like 10^{-1}, 10^{-3}, 10^{-6}, 10^{-10}, 10^{-15} and 10^{-20} and got the power consumption values. The algorithm stops if the average relative change in the best fitness function value over the iterations is less than or equal to function tolerance. When the function tolerance value decreases; as can be seen from Figure 5.19, power consumption decreases until 10^{-6} and after that does not change much. It is because 10^{-6} is enough for the algorithm. Less than 10^{-6} is unnecessary over-precision. More than that value causes premature termination of the algorithm. Therefore, 10^{-6} is the optimum function tolerance value.

The other parameter of particle swarm optimization algorithm we examined is maximum iteration. For maximum iteration, we set the number of base stations to 5 and the number of users to 15. We have tried different maximum generation values like 750, 1875, 3750, 5625, 7500, 15000 and 25000.

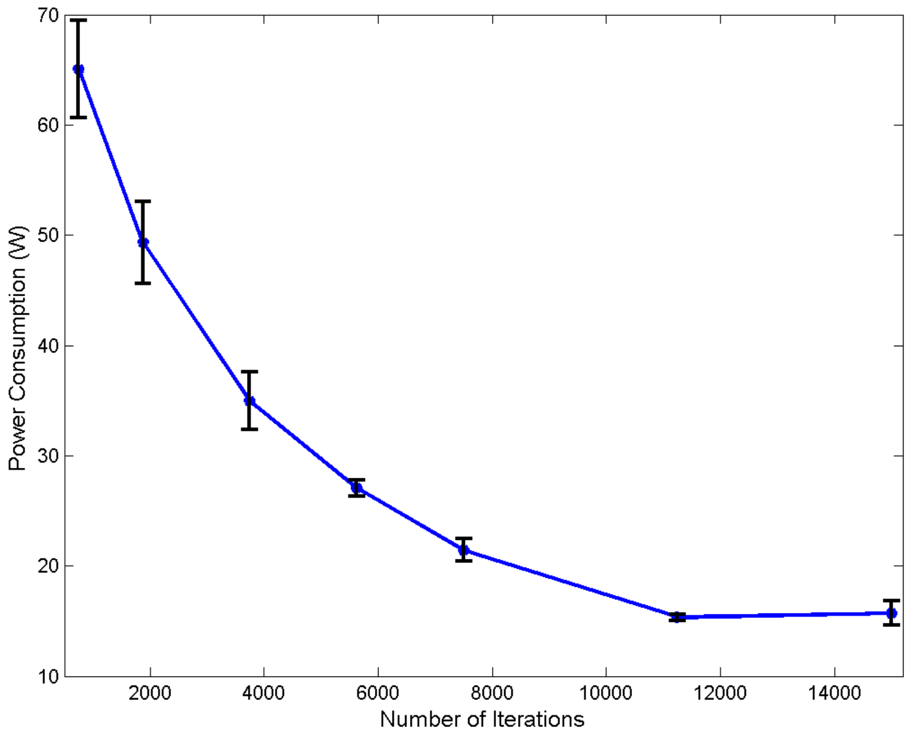

Figure 5.20: Power consumption values for different maximum iteration values.

Figure 5.21 shows that running time increases with the maximum iteration value. However, as Figure 5.20 illustrates, after 15000 maximum iterations, increasing maximum iteration value does not have an effect on the power consumption value. Therefore, the optimum value for maximum iterations to reach the required result is 15000, which is $200 \times M \times N$ for this case.

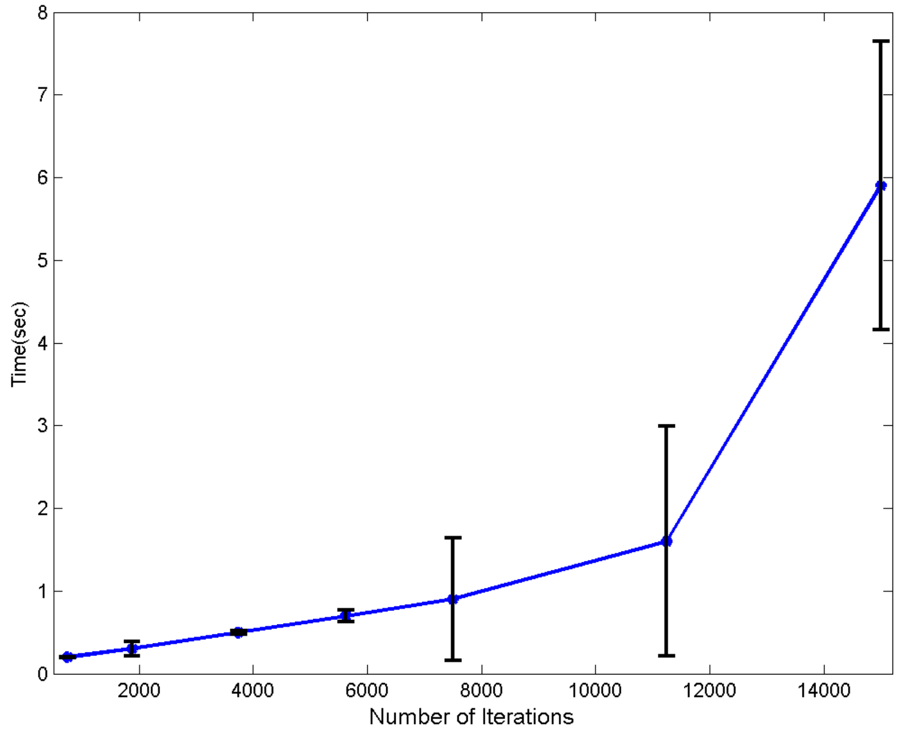

Figure 5.21: Running time values for different maximum iteration values.

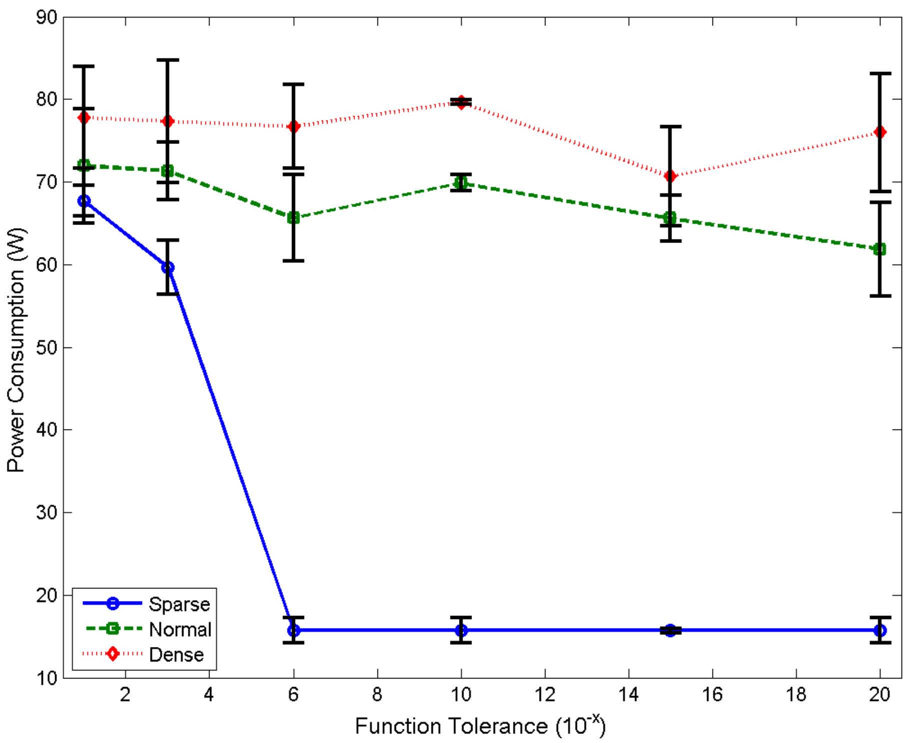

Figure 5.22: Function tolerance effects on power consumption.

5.5.3 Impacts of Simulated Annealing Algorithm Parameters

We observed the impacts of different simulated annealing algorithm parameters over the proposed optimization model.

We tried different function tolerance values like 10^{-1}, 10^{-3}, 10^{-6}, 10^{-10}, 10^{-15} and 10^{-20} and got the power consumption values. The algorithm stops if the average relative change in the best fitness function value over the iterations is less than or equal to function tolerance. When the function tolerance value decreases; as can be seen from Figure 5.22, power consumption decreases until 10^{-6} and after that does not change much. It is because 10^{-6} is enough for the algorithm. Less than 10^{-6} is unnecessary over-precision. More than that value causes premature termination of the algorithm. Therefore, 10^{-6} is the optimum function tolerance value.

5.5.4 Impacts of Pattern Search Polling Algorithm Parameters

We observed the impacts of different pattern search polling algorithm parameters over the proposed optimization model.

We tried different function tolerance values like 10^{-1}, 10^{-3}, 10^{-6}, 10^{-10}, 10^{-15} and 10^{-20} and got the power consumption values. The algorithm stops if the average relative change in the best fitness function value over the iterations is less than or equal to function tolerance. When the function tolerance value decreases; as can be seen from Figure 5.23, power consumption decreases until 10^{-6} and after that does not change much. It is because 10^{-6} is enough for the algorithm. Less than 10^{-6} is unnecessary over-precision. More than that value causes premature termination of the algorithm. Therefore, 10^{-6} is the optimum function tolerance value.

The other parameter of pattern search polling algorithm we examined is maximum iteration. For maximum iteration, we set the number of base stations to 5 and the number of users to 15. We have tried different maximum generation values like 750, 1875, 3750, 5625, 7500, 15000 and 25000.

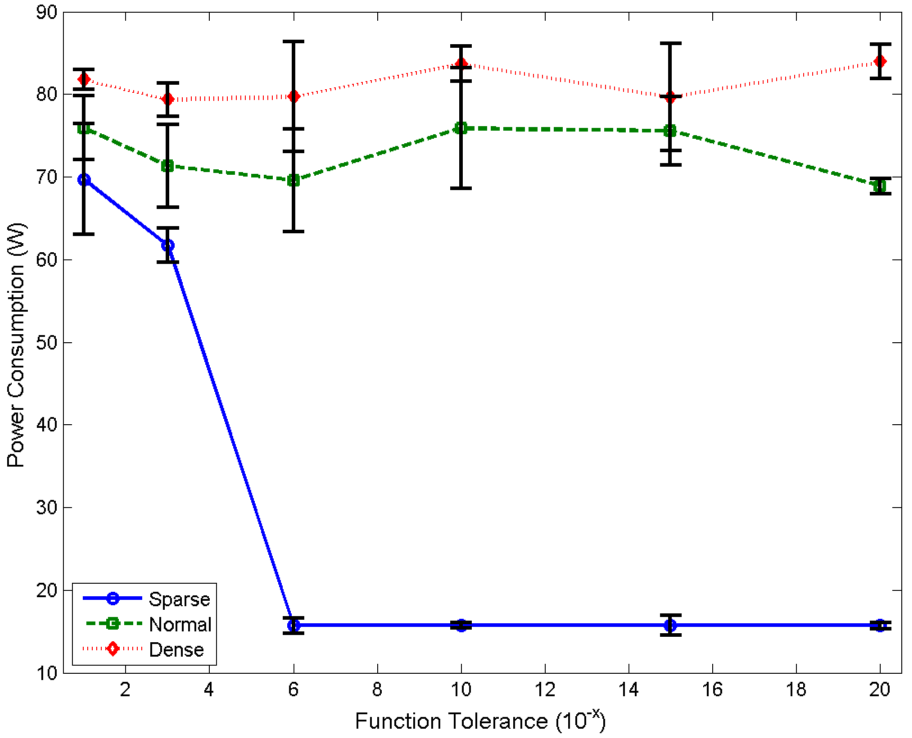

Figure 5.23: Function tolerance effects on power consumption.

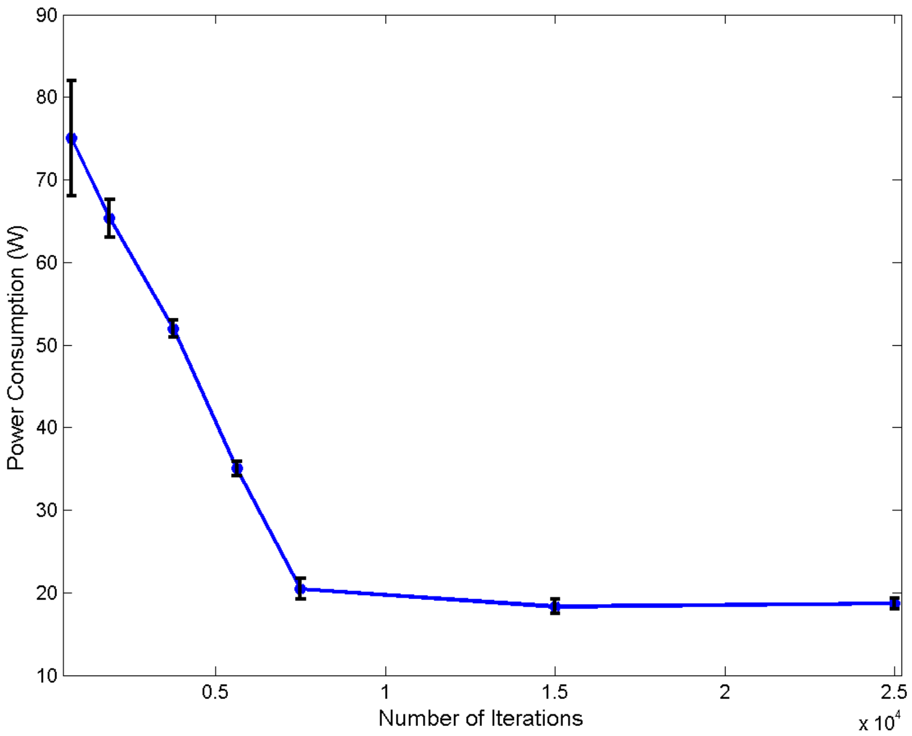

Figure 5.24: Power consumption values for different maximum iteration values.

Figure 5.25 shows that running time increases with the maximum iteration value. However, as Figure 5.24 illustrates, after 7500 maximum iterations, increasing maximum iteration value does not have an effect on the power consumption value. Therefore, the optimum value for maximum iterations to reach the required result is 7500, which is $100 \times M \times N$ for this case.

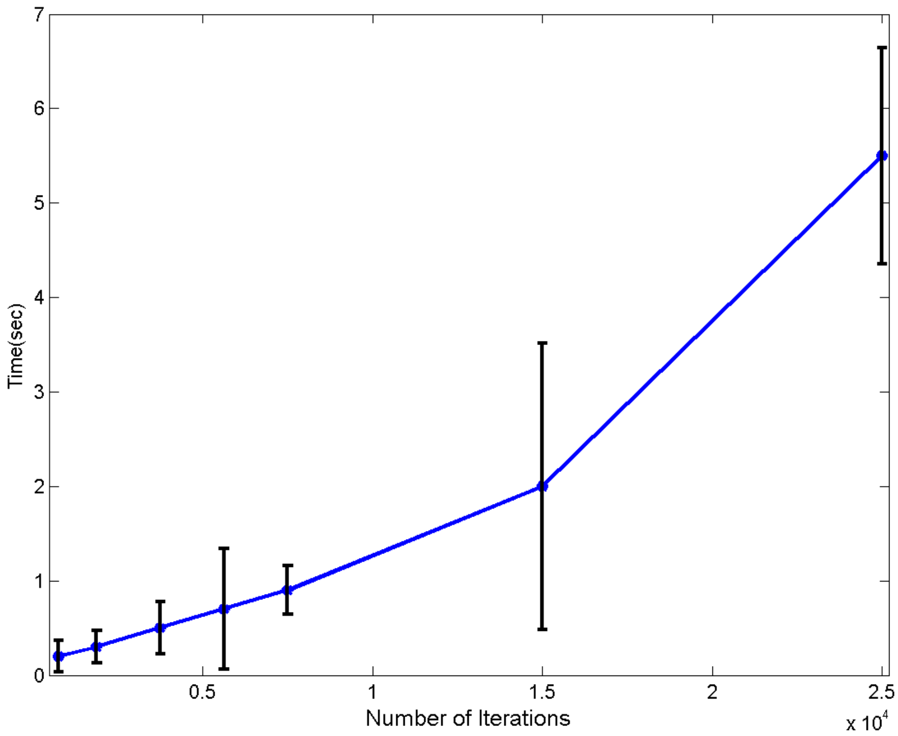

Figure 5.25: Running time values for different maximum iteration values.

5.5.5 Comparison of Meta-Heuristics

Finally, we solved the problem using some meta-heuristics of MATLAB Global Optimization Toolbox to find out which one is the best for solving our optimization problem.

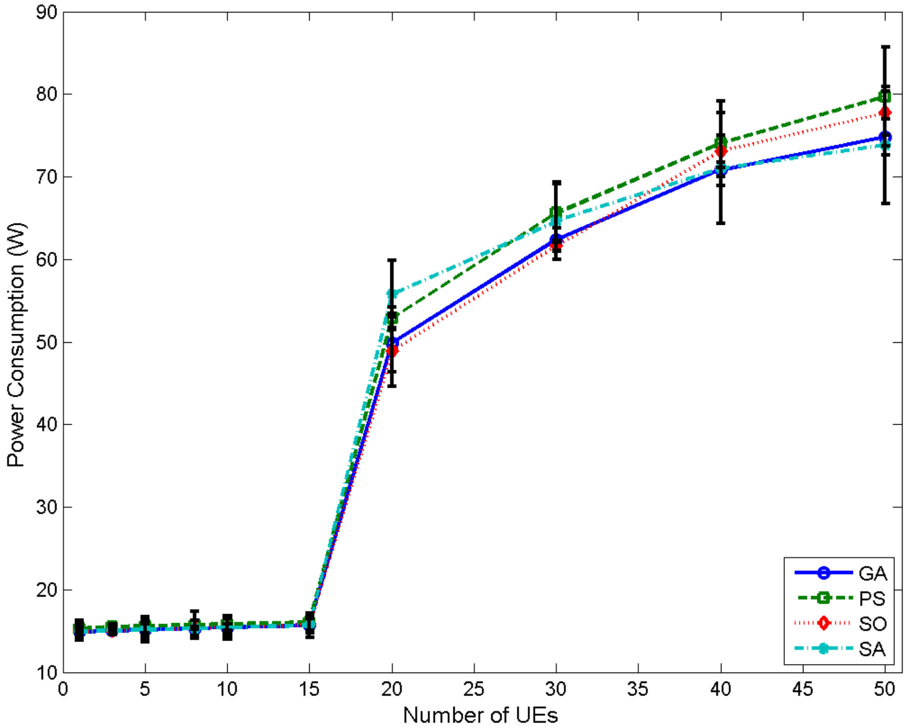

Figure 5.26: Power consumption values for different optimization methods for 5 BSs.

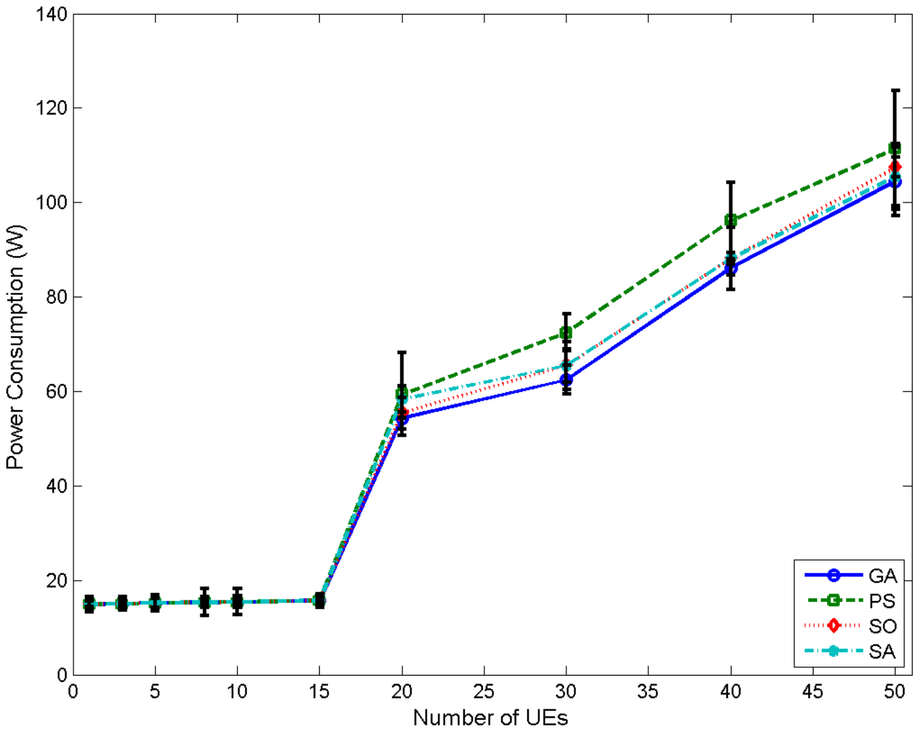

Figure 5.27: Power consumption values for different optimization methods for 10 BSs.

As can be seen from Figure 5.26, Figure 5.27, Figure 5.28 and Figure 5.29, power optimization values and running times of these algorithms are very close. In Figure 5.27, it is illustrated that genetic algorithm gives best results for all cases for 10 BSs. In Figure 5.26, particle swarm has better power consumption value for 20 and 30 UEs and simulated annealing has better power consumption value for 50 UEs for 5BSs. However, in Figure 5.28 and Figure 5.29, these algorithms have worse running time values than genetic algorithm. On the other hand, pattern search polling algorithm has better running time values in Figure 5.28 for 30 and 50 UEs and in Figure 5.29 for 30, 40 and 50 UEs, nevertheless, as Figure 5.26 and Figure 5.27 represent, pattern search has much worse power consumption values. Therefore, genetic algorithm is the most suitable choice for our optimization problem.

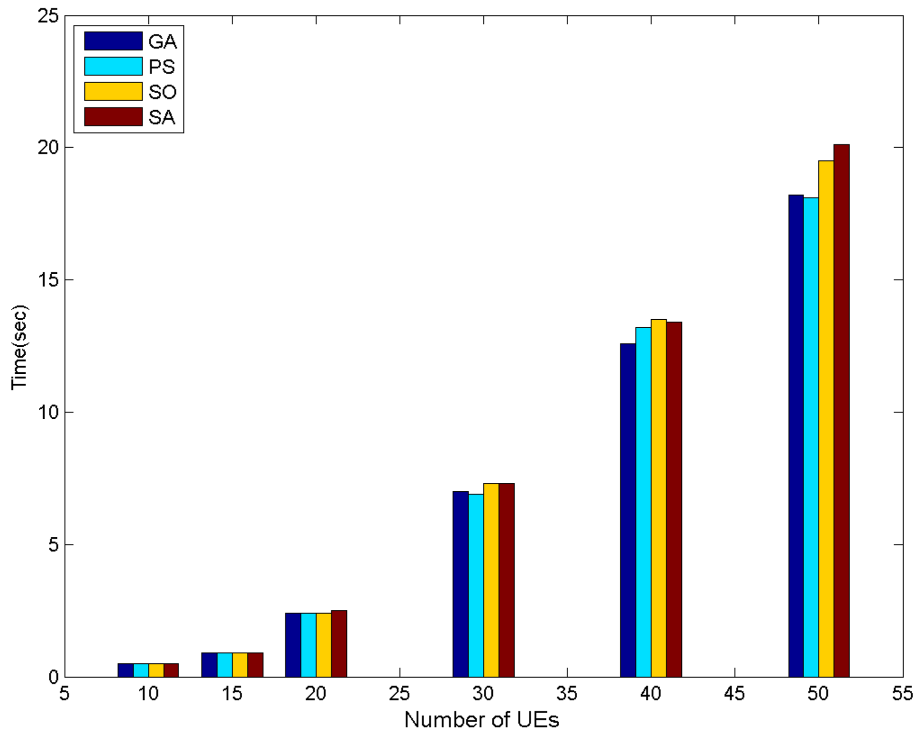

Figure 5.28: Running time values for different optimization methods for 5 BSs.

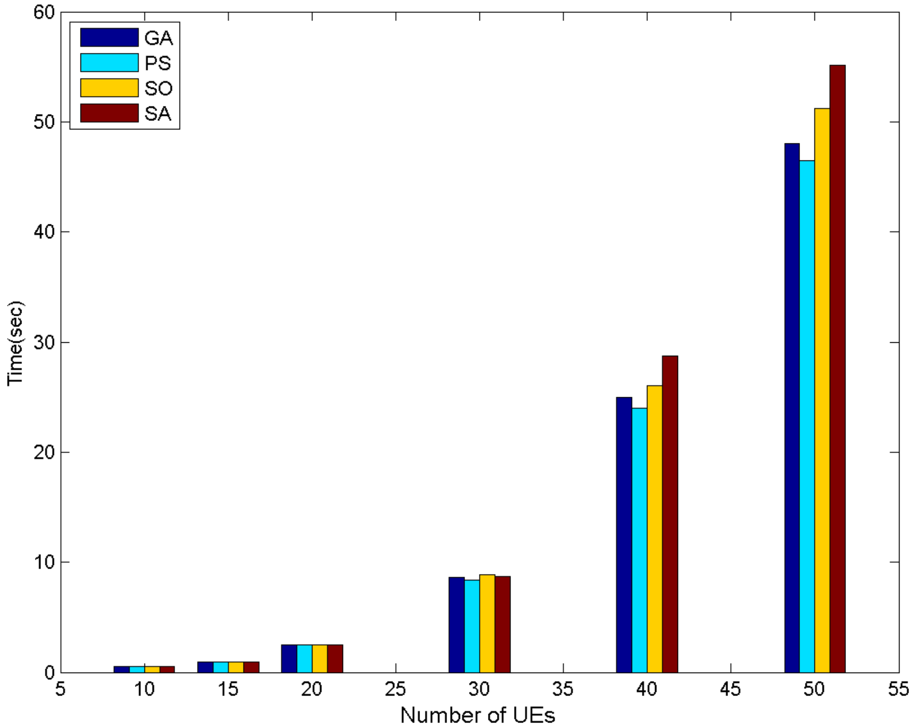

Figure 5.29: Running time values for different optimization methods for 10 BSs.

CHAPTER 6

CONCLUSION

In this thesis, we proposed a user satisfaction aware cell zooming and base station scheduling algorithm to reduce energy consumption and enhance the quality of service in a mobile network. In the proposed algorithm, we adapt transmit power of active base stations based on network condition and turn off redundant base stations while user satisfaction is improved. In this work we defined an optimization problem and solve it with the genetic algorithm which causes a significant reduction in energy consumption in comparison with the basic model. We have tested our solution for various base station and user equipment densities. Then, we compared our result with another optimization model, the model that is proposed in [5]. After that, we have done impact analysis of system parameters and genetic algorithm parameters to our solution in terms of power consumption value and user satisfaction percentage value. Finally, we have solved the problem by using other MATLAB meta-heuristic functions, pattern search polling, particle swarm optimization and simulated annealing, and compare the power consumption values that these algorithms generated and running time values with the values of genetic algorithm.

According to results, there are several conclusions that can be made:

- Our solution provides excessive power preservation according to the basic not-optimized model that all BSs are always active and work with full power. Our solution conserves up to 90% power for 10 BSs and less than 15 UEs with respect to the basic model.

- Our solution stayed a little behind of the algorithm introduced in [5] in terms of energy conservation. They conserved up to 5% energy with respect to the proposed algorithm due to the lack of some constraints such as outage probability and choosing the best BS for each UE. However, again, because of these constraints, our algorithm can improve the UE satisfaction up to 47%.

The proposed solution is capable of reducing the power consumption while overseeing the quality of service. On the other hand, there are some parts that can be improved in this thesis:

- This solution can be adapted to larger environments and more complex channel models can be used.
- The environment can be designed with heterogeneous networks and the solution can be distinguished for different kinds of BSs.
- Green energy sources can be integrated into the solution to reduce the energy consumption.
- This solution can be combined with the proposals that recommend traffic prediction solutions to reduce the power consumption and be made proactive.

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