ASHRAF SHERIF

BIO-INSPIRED ENERGY OPTIMIZATION FOR TWO-TIER WIRELESS COMMUNICATION NETWORKS

PhD THESIS

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NEAR EAST UNIVERSITY

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DEPARTMENT OF DEPARTMENT OF ELECTRICAL AND ELECTRONIC ENGINEERIG

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DOCTORAL THESIS

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Supervisor

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Nicosia

June, 2023

Approval

We certify that we have read the thesis submitted by Ashraf Abdalla Ahmed Sherif titled **"Bio-inspired energy optimization for two-tier wireless communication networks"** and that in our combined opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Doctor of Philosophy.

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Declaration

I hereby declare that all information, documents, analysis and results in this thesis have been collected and presented according to the academic rules and ethical guidelines of Institute of Graduate Studies, Near East University. I also declare that as required by these rules and conduct, I have fully cited and referenced information and data that are not original to this study.

Ashraf Sherif

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Ashraf Sherif

Abstract

Bio-inspired Energy Optimization for Two-tier Wireless Communication Networks

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Energy efficiency has attracted attention from researchers in wireless communications, as it is essential to guaranteeing quality of service (QoS). where the energy consumption of future wireless communication networks has become one of the most challenging issues. Wireless heterogeneous networks (HetNets) are one of the promising methods in fifth-generation (5G) cellular networks to meet the ever-increasing demand for data traffic. Increased coverage can be achieved by adding more base stations, but the operation consumes a lot of power. In two-tier networks, different types of small cell base stations (SCBs) coordinate with macro cell base stations (MCBs) to maintain wider coverage indoors and outdoors. A significant lack of studies has been conducted on enhancing network spectrum efficiency (SE) and maximizing energy efficiency (EE) by adjusting SCB power consumption using bias function values and bio-inspired energy optimization. The movement of users' equipment (UEs) also leads to the experience of light traffic loads on some SCBs, resulting in coverage gaps if several of these SCBs are turned off in a particular area. Thus, to address the aforementioned research gap, this thesis presents a novel bio-inspired energy optimization algorithm named Grasshopper Optimization Algorithm-based Variant Power Mode Selection (GOA-VPMS), which selects the appropriate mode of operation for small cell base stations (SCBs). With our novel algorithm, SCBs can have their operation mode extended into four different modes: on, standby, sleep, and off. Calculations are made for a two-tier network's, signal-to-interference noise ratio (SINR), user-SCB association index, power consumption, spectrum efficiency, and energy efficiency for the proposed system. The ranking mechanisms used in this study to classify UEs based on the metric of received signal strength (RSS), while the bias function controls the power consumption of SCBs under certain constraints. Next we formulate the EE maximization problem under a set of constraints and solve it with our novel proposed algorithms, GOA-VPMS. The concept of control data separation architecture (CDSA) is considered in this study, where the MCB controls the entire network and an average inactive ratio threshold is used to tackle the second issue, guarantee coverage, and overcome the coverage holes that may occur when switching off many SCBs in a certain area. For evaluation, we conducted experiments and compared them with previous alternative works. The findings show that the GOA-VPMS algorithm can improve performance and achieve higher SE and EE for the two-tier network, outperforming alternative techniques.

Key Words: two-tier network, energy efficiency (EE), bias function, Grasshopper Optimization Algorithm (GOA).

Özet

İki Katmanlı Kablosuz İletişim ağları için Biyo-ilhamlı Enerji Optimizasyonu

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Enerji verimliliği, hizmet kalitesini (QoS) garanti etmek için gerekli olduğundan, kablosuz iletişim alanındaki araştırmacıların dikkatini çekmiştir. geleceğin kablosuz iletişim ağlarının enerji tüketiminin en zorlu konulardan biri haline geldiği yer. Kablosuz heterojen ağlar (HetNets), sürekli artan veri trafiği talebini karşılamak için beşinci nesil (5G) hücresel ağlarda umut vaat eden yöntemlerden biridir. Daha fazla baz istasyonu eklenerek daha fazla kapsama alanı elde edilebilir, ancak işlem çok fazla güç tüketir. İki katmanlı ağlarda, farklı türde küçük hücre tabanları (SCB'ler), iç ve dış mekanlarda daha geniş bir kapsama alanı sağlamak için makro hücre tabanlarıyla (MCB'ler) koordine edilir. Önyargı işlevi değerleri ve biyo-ilhamlı enerji optimizasyonu kullanarak SCB'lerin güç tüketimini ayarlayarak ağ spektrum verimliliğini (SE) ve enerji verimliliğini (EE) en üst düzeye çıkarmaya yönelik önemli bir çalışma eksikliği yapılmıştır. Kullanıcı ekipmanlarının (UE'ler) hareketi ayrıca bazı SCB'lerde hafif trafik yükleri deneyimine yol açar ve bu SCB'lerden birkaçı belirli bir alanda kapatılırsa kapsama boşluklarına neden olur. Bu nedenle, yukarıda belirtilen araştırma boşluğunu gidermek için bu tez, küçük hücreli baz istasyonları (SCB'ler) için uygun çalışma modunu seçen, Grasshopper Optimization Algorithm-based Variant Power Mode Selection (GOA-VPMS) adlı yeni bir biyo-ilhamlı enerji optimizasyon algoritması sunmaktadır.). Yeni algoritmamızla, SCB'ler çalışma modlarını dört farklı moda genişletebilir: açık, bekleme, uyku ve kapalı. Önerilen sistem için iki katmanlı bir ağın, sinyal-parazit gürültü oranı (SINR), kullanıcı-SCB ilişkilendirme indeksi, güç tüketimi, spektrum verimliliği ve enerji verimliliği için hesaplamalar yapılmıştır. Önyargı işlevi, belirli kısıtlamalar altında SCB'lerin güç tüketimini kontrol ederken, alınan sinyal gücü (RSS) metriğine dayalı olarak UE'leri sınıflandırmak için sıralama mekanizmalarını kullanıyoruz. Daha sonra, EE maksimizasyon problemini bir dizi kısıtlama altında formüle ediyoruz ve yeni önerilen algoritmalarımız GOA-VPMS ile çözüyoruz.

Kontrol veri ayırma mimarisi (CDSA) kavramı, makro hücre baz istasyonunun tüm ağı kontrol ettiği ve ikinci sorunun üstesinden gelmek, kapsamı garanti etmek ve oluşabilecek kapsama boşluklarının üstesinden gelmek için ortalama bir etkin olmayan oran eşiğinin kullanıldığı bu araştırmada ele alınmıştır. belirli bir alanda çok sayıda SCB'yi kapatırken. Değerlendirme için deneyler yaptık ve bunları önceki alternatif çalışmalarla karşılaştırdık. Bulgular, GOA-VPMS algoritmasının alternatif teknikleri geride bırakarak iki katmanlı ağ için daha yüksek EE ve SE'yi geliştirebileceğini ve elde edebileceğini göstermektedir.

Anahtar kelimeler: iki katmanlı ağ, enerji verimliliği (EE), önyargı işlevi, Çekirge Optimizasyon Algoritması (GOA).

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List of Abbreviations

Abbreviation	Definition
2G	Second Generation Cellular Networks
3G	Third Generation Cellular Networks
4G	Fourth Generation Cellular Networks
5G	Fifth Generation Cellular Networks
5grEEn	Toward Green 5G Mobile Networks
BCG2	Beyond Cellular Green Generation
BS	Base Station
CDSA	Control Data Separation Architecture
CO2	Carbon dioxide
CPU	Central Processing Unit
EE	Energy Efficiency
GA	Genetic Algorithm
GHG	Greenhouse Gas
GOA	Grasshopper Optimization Algorithm
HetNet	Heterogeneous Network
HO	Handover
LTE	Long Term Evolution
LTE-A	Long Term Evolution Advanced
MABs	Multiple Access Points
MCB	Macro Cell Base Station
METIS	Mobile Enablers Twenty Information Society
MIMO	Multiple Input Multiple Output
MiWEBA	Millimetre-Wave Evolution for Backhaul and Access
OPEX	Operational Expenditure
PCS	Power Control Strategies

PMVS	Power Mode Variant Selection
PPP	Poisson Point Process
PSO	Particle Swarm Optimization
QoS	Quality of Service
RF	Radio Frequency
RSS	Received Signal Strength
RSSI	Received Signal Strength Indecator
SCB	Small Cell Base Station
SE	Spectrum Efficiency
SONs	Such as self-optimization networks
SI	Swarm Intelligent
SINR	Signa-to-interference-plus-noise Ratio
SODUA	Switching Off Decision and User Association
TCXO	Temperature Compensated Crystal Oscillators
VPMS	Variant POWER Mode Selection
$\boldsymbol{h}$	Small scale fading (SSF) coefficients of the channel
$\boldsymbol{U}$	Set of UE's
$\boldsymbol{\eta}$	Calculated Energy Efficiency
$\boldsymbol{S}$	Set of SCBs
$\boldsymbol{R_{total}}$	Total Data Rate of all SCBs
$\boldsymbol{P_s}$	Transmit Power of SCB
$\boldsymbol{P_m}$	Transmit Power of MCB
$\bar{\boldsymbol{\Psi}}$	Average Sleeping Ratio
$\boldsymbol{r_{in}}$	Inactive radius
$\boldsymbol{d_{su}}$	Distance between u UE's to the associated s SCB
$\boldsymbol{\alpha}$	Path loss exponent
$\boldsymbol{P_m^t}$	Total power consumption of the MCBs

$\boldsymbol{P_s^t}$	Total power consumption of the SCBs
$\boldsymbol{W}$	Frequency bandwidth of each s SCB and u UE's link
$\boldsymbol{D}$	Coverage of MCB
$\boldsymbol{N0}$	Additive white Gaussian noise (AWGN)
$\boldsymbol{p_m^t}$	Static Power Consumption of MCB
$\boldsymbol{p_s^t}$	Static Power Consumption of SCB
$\boldsymbol{\xi}^*$	Optimum Bias function Value
$\boldsymbol{\xi_{on}^m}$	Bias for Macro BS On
$\boldsymbol{\xi_{on}^s}$	Bias for Small Cell BS On
$\boldsymbol{\xi_{sby}^s}$	Bias for Small Cell BS Standby
$\boldsymbol{\xi_{slp}^s}$	Bias for Small Cell BS Sleep
$\boldsymbol{\xi_{of}^s}$	Bias for Small Cell BS Off

CHAPTER I

Introduction

This chapter provides an introduction to the challenges facing wireless communication systems and the gap between the state of the art. It also describes the purpose of the study, research hypotheses, research aims, the contribution of this study, its importance, its limitations, and related descriptions of the research.

Energy efficiency is becoming increasingly important in wireless communication systems, where reducing the power consumption of wireless network base stations has received significant attention because it accounts for a significant portion of total energy consumption in information and communication technology (ICT) (Kang et al., 2017). For the reader's convenience, the following explanation is provided to present an overview of how small BSs work. Multiple BSs with different ranges of transmit power make up a heterogeneous network. In two-tier networks, macrocell base stations (MCBs) allow the power consumption of small cell BSs to be effectively used and managed, particularly during communication between BSs and mobile users (Han et al., 2016). There is only one cell association considered in this thesis. Due to the fact that mobile users can only be associated with one macro BS at a time, despite the fact that there are many macro BSs in the network, they cannot be associated with more than one macro BS. As a consequence of signal loss during signal transmission, there is no guarantee that a mobile user will receive the same quality of service (QoS) from a given macro BS when moving from one location to another. Consequently, the deployment of small BSs that enables the macro BS to extend its coverage area. Macrocells cover an area of about 30 kilometers in radius and are the largest cells. Small cells, however, cover a smaller area than macrocells, depending on their category. This, in turn, improves the capacity of macrocell networks by offering better and wider coverage, which is one of the characteristics of small BSs. A small cell can be classified into different categories, such as microcell, picocell, and femtocell. Femtocells are the smallest category, designed for use at home with easy installation. Picocells are medium-sized small cell that are most often deployed by service providers in buildings to cover high-density areas, also known as hotspots, while microcell is the largest small cell, and they are usually used on the street (Yan et al., 2017). Nevertheless, the uncoordinated deployment and improper planning of small BSs in macrocell networks result in heavy traffic congestion, energy inefficiency, high operational costs, and intercell interference (Argyriou et al., 2016).

Statement of the Problem

The significance of energy efficiency shortcomings in two-tier wireless communication networks is as follows:

- Increasing operational costs: Two-tier wireless communication networks require more base stations, which increases operational costs for network operators. These costs can be significantly influenced by the energy consumption of these base stations.
- Impact on the environment: Two-tier wireless communication networks' increased energy consumption can lead to a higher carbon footprint, causing the environment to be degraded.
- Battery life is limited: Small cells in two-tier wireless communication networks can deplete their batteries more quickly, making battery replacement more frequent and expensive.
- Instability of the network: A two-tier wireless communication network’s energy consumption can also impact the network's stability. It can result in network congestion, data loss, and decreased network performance if there is an insufficient energy supply for base stations.
- User experience: Keeping two-tier wireless communication networks energy-efficient can also affect users' experiences, as a poorly optimized network may cause dropped calls, slow data speeds, and other connectivity problems.
- As the demand for data transmission and mobile devices grows, wireless communication systems are becoming more popular. However, these systems are highly energy-intensive and require a lot of power to operate. As a result, these systems need to optimize their energy consumption to reduce their environmental impact and operational costs.
- Changes in the number of users, traffic demand, and network topology are all examples of dynamic network conditions in two-tier wireless communication networks. These changes can cause fluctuations in energy consumption, making the development of a stable and efficient energy optimization solution difficult.
- Trade-off between energy efficiency and network performance: When optimizing the energy efficiency of a two-tier wireless communication network, the network's performance may suffer as a result. It is therefore necessary to balance these two factors to ensure an optimal solution, for

example (Yang et al., 2017), to maximize the performance of the energy efficiency system at the expense of the spectrum efficiency system.

Overall, a two-tier wireless communication network's energy efficiency shortcomings can have a significant impact on the network's overall performance, operational costs, and user experience. As a result, it is critical to create energy-efficient solutions that optimize a two-tier wireless communication network's energy consumption while minimizing its environmental impact. Sleeping BS strategies could aid in reducing overall network power consumption. Nonetheless, less work was done to assess the overall network's energy efficiency performance. Additionally, there is also the potential to improve the overall energy efficiency of a network through the implementation of BS sleeping strategies in a separation architecture. However, the current studies have several flaws in terms of providing a higher energy efficiency that takes into account certain constraints. The BS sleeping strategy is the most commonly used technique and algorithm among researchers in this field. In one recent study (X. Chai et al., 2018), the aim was to reduce the power consumption of BSs in a heterogeneous network by using sleeping strategies. Another study, on the other hand, only used two types of sleeping strategies (random and strategic) on macro-BSs to maximize energy efficiency in a homogeneous network, also known as a one-tier network (Y. S. Soh et al., 2013). However, the authors distributed femtocells in the macrocell network's coverage region not to maximize energy efficiency but instead to offer better coverage. In our opinion, there has been very little research on how to maximize the energy efficiency of a two-tier network that includes the probability of activating the BSs with BS sleeping strategies in order to maximize energy efficiency. Therefore, this thesis aims at looking at methods to improve the energy efficiency of a two-tier network as a result of the necessity to do so. There are several small BSs that are lightly equipped as a result of the mobility of mobile users, which means that a small BS will only serve a few mobile users at a time (Hoydis et al., 2011). Despite this, small BSs still consume some energy. As a result, in previous works, the BS sleeping strategy was proposed in order to reduce power consumption by putting specific BSs into sleep mode based on some criteria. However, this strategy resulted in coverage holes where network coverage was not guaranteed (Wu et al., 2017). As a consequence of the coverage gaps, some users were unable to connect to any small BSs. On the other hand, an approach that has been proposed to solve this problem is the separation architecture, also known as the control data separation architecture (CDSA), which is composed of a macro-BS and several smaller BSs. It should be noted that throughout the architecture, the macro-BS is responsible for all network activities, including those of the small BSs within its coverage area (R. I. Ansari et al., 2019). The sleeping mode consumes about 10% of the total amount of power consumed, whereas the switching off mode consumes almost no power (Capone et al., 2012). To investigate the overall network energy efficiency performance, a study using a CDSA and considering switching on and off strategies is required. The drawback of turning off BSs is that the wake-up time is longer compared to using sleeping BSs when required (C. Liu et al., 2015). As a consequence, it is better to consider different sleeping modes for a BS that would allow only the necessary small BSs to be sent to off mode.

Purpose of the Study

Energy optimization for two-tier wireless communication networks is one of the purposes of the research study, which is to develop techniques and algorithms that can assist in reducing the energy consumption of wireless communication networks while at the same time maintaining or improving their performance. Two-tier wireless communication networks consist of two layers: macrocells and small cells, the macro-cell layer covers a large area and serves a large number of users (Yang et al., 2015). In contrast, the small cell layer covers a lesser area and serves a smaller number of users. The small cell layer is typically used to offload traffic from the macrocell layer and provide better coverage and capacity in dense urban areas. Energy consumption is a critical issue in wireless communication networks, particularly small cell networks. Small cells are typically deployed in areas with high user density, and their energy consumption can be significant. By optimizing the energy consumption of small cell networks, the operational costs of wireless communication networks can be reduced and make them more environmentally friendly. Optimizing the energy consumption of a two-tier wireless communication network involves developing algorithms that can optimize the energy consumption of the network while maintaining or improving its performance at the same time (Elhabyan et al., 2015). This can involve optimizing the transmit power of the base station, scheduling the transmission of data packets, and optimizing the placement of small cells.

In general, the main objective of studying energy optimization for two-tier wireless communication networks is to develop an efficient and sustainable wireless communication network that will be able to meet the demand for high-speed data transmission while also reducing the environmental impact of these networks.

Research Hypotheses

The purpose of this study is to verify the hypothesis that

I. By applying a novel energy optimization algorithm to two-tier wireless communication networks, the overall power consumption can be reduced, saving more energy.

II. With a novel energy optimization algorithm applied to two-tier wireless communication networks, the overall energy efficiency can be improved, subsequently improving the quality of service (QoS) for users.

III. By applying a novel energy optimization algorithm to two-tier wireless communication networks, the overall spectrum efficiency can be enhanced, resulting in better quality of service (QoS) for users.

IV. By fixing one bias function value and relaxing the others, the energy efficiency is still optimized.

Research Goals

The objectives of this study are as follows:

I. Aims to meet the increase in demand for wireless communication and reduce the energy consumption of communication networks.

II. To propose an algorithm for optimizing the energy efficiency of two-tier wireless communication networks under the concept of CDSA architecture.

III. To employ bias function values in each small cell BS to control the power consumption.

IV. Solve the optimization problem using the proposed algorithm and the bias factors employed in each BS mode.

V. Utilizing an average inactive ratio threshold in a two-tier wireless network to guarantee coverage and avoid coverage gaps.

VI. To demonstrate that the bio-inspired algorithm can significantly improve the energy efficiency and enhance the spectrum efficiency of two-tier wireless communication networks while maintaining the quality of service for users.

Research Contributions

The contributions of this study are summarized below:

- proposing a bio-inspired mechanism that determines the optimal mode of operation for each SCB to maximize the efficiency of two-tier wireless networks based on its operation mode (on, standby, sleep, or off). The study introduces a bias function to manage power consumption and applies a minimization algorithm accordingly.
- The study also applies GOA to determine the optimal bias function values for a two-tier network that maximizes EE, which cooperates with the proposed algorithm called Variant Power Mode Selection (VPMS) to select the appropriate operating mode for each SCB. Based on the ranking mechanism proposed in GOA-VPMS, the proposed algorithm computes EE, while the bias function is used to regulate the power consumption of SCBs under several limitations.
- A threshold for average inactive ratios is also used to ensure coverage and prevent coverage gaps.
- The study calculates several metrics to provide insight into the proposed network's performance, including SINR, RSS, user association index, power consumption per BS, SE, and EE.
- Generally, the study seeks to evaluate the performance of our proposed algorithm, GOA-VPMS, and compare it with existing energy optimization techniques, such as those described in (Baidowi, et al. 2021).

In addition, throughout this study, it is assumed that the Control Data Separation Architecture (CDSA) is used, whereas the main benefit of this system is that it offers a way to control all activities of the network, especially when sending SCBs into sleep mode, off mode, or even just leaving them on at all times. As a result of this, SE and EE are expected to improve significantly.

Definitions of terms

Chapter 2, is divided into two sections: a theoretical framework and related research. The theoretical framework presents background information about homogeneous, heterogeneous, and swarm intelligences**. Chapter 3**, is on methodology and contains subsections: system model, channel model, the expression of signal-to-interference-plus-noise ratio (SINR), achievable data rate, calculation of power consumption, the mechanism of classification, problem statement and solution, the algorithm VPMS, the proposed algorithm GOA-VPMS, and finally, the performance evaluation methods. **Chapter 4**, describes the simulation and results and compares them with existing algorithms. Our thesis ends with **Chapter 5**, which presents a conclusion and future research suggestions.

CHAPTER II

Fundamental Concepts and Literature Review

In this chapter, a brief overview of related conceptual definitions, descriptions, and information related to research already exists in the literature is presented.

Fundamental Concepts

Wireless networks

Wireless networks have revolutionized the way people communicate and connect in the modern world. These networks, often referred to as Wi-Fi or cellular networks, rely on wireless signals to transmit data, enabling a vast range of devices to communicate without the need for physical cables. Wireless networks have become an integral part of our daily lives, spanning from our homes and workplaces to public spaces and beyond (Pahlavan et al., 2021). The evolution of wireless networks has seen several generations of technology, each offering improved performance and capabilities. Starting with the early 2G (second generation) networks, which primarily enabled voice communication, wireless technology has rapidly advanced to 3G, 4G LTE, and now 5G. Each new generation has brought faster data speeds, reduced latency, and greater capacity, allowing for more data-intensive applications, such as video streaming, online gaming, and the Internet of Things (IoT). Wireless networks operate on a foundation of radio frequency (RF) technology, which involves the transmission and reception of electromagnetic waves (Zhou & Ye. 2021). These waves carry data in the form of modulated signals, allowing devices like smartphones, laptops, and smart appliances to communicate with each other and access the internet. Key components of wireless networks include access points, routers, and cellular base stations, which serve as connection points and relay data between devices and the broader network infrastructure (Li et al., 2018).

The proliferation of wireless networks has enabled unprecedented levels of mobility and connectivity, transforming industries such as healthcare, transportation, and entertainment. However, this growth has also presented challenges, including concerns about security, network congestion, and the need for ongoing spectrum management to support the ever-increasing demand for wireless data. Ongoing research in the field of wireless networks focuses on improving network efficiency (Giordani et al., 2020).

Fifth Generation (5G)

The fifth generation of wireless technology, commonly referred to as 5G, represents a significant leap forward in the evolution of telecommunications and mobile networks. It builds upon the foundations laid by previous generations (2G, 3G and 4G) but introduces several key advancements that promise to revolutionize the way people connect, communicate, and interact with digital technology (Stallings et al., 2021). Key features and characteristics of 5G include:

1. **Higher Data Speeds:** 5G networks offer vastly improved data speeds compared to their predecessors. This technology can deliver peak data rates of up to 20 Gbps (gigabits per second), significantly faster than 4G LTE, enabling seamless streaming of high-definition video, ultra-fast downloads, and real-time online gaming.
2. **Low Latency:** 5G networks bring ultra-low latency, reducing the delay between sending a request and receiving a response. This is critical for applications like autonomous vehicles, remote surgery, and augmented/virtual reality experiences, where split-second responses are essential.
3. **Increased Network Capacity:** With 5G, networks can handle a substantially larger number of devices simultaneously. This capacity boost is essential for the growing number of IoT devices, smart cities, and densely populated areas.
4. **Enhanced Reliability:** 5G networks are designed to provide greater reliability and resilience, ensuring consistent connectivity even in challenging environments.
5. **Network Slicing:** This feature allows network operators to create multiple virtual networks within the same physical infrastructure. It's particularly valuable for accommodating various use cases, from mission-critical applications to IoT devices, each with unique requirements.
6. **Millimeter Wave (mmWave) Spectrum:** 5G utilizes higher-frequency spectrum, including mmWave bands, to transmit data. While these frequencies enable faster speeds, they have shorter range and may require more infrastructure, including small cells, to provide widespread coverage.

7. **Massive MIMO:** Multiple-Input, Multiple-Output (MIMO) technology with a large number of antennas improves network efficiency and capacity, especially in crowded areas.
8. **Energy Efficiency:** 5G networks aim to be more energy-efficient than their predecessors, aligning with environmental sustainability goals.

5G is expected to have a transformative impact on various industries, including healthcare, manufacturing, transportation, and entertainment (Gohar et al., 2021). It will enable innovations like telemedicine, autonomous vehicles, smart factories, and immersive augmented reality experiences. However, the rollout of 5G also brings challenges, such as the need for extensive infrastructure upgrades, including small cell deployments, and addressing concerns about privacy and security in an increasingly connected world. Researchers and engineers continue to work on optimizing 5G technology, while discussions about the future evolution of wireless networks, including 6G, are already underway to meet the demands of tomorrow's digital society (Viswanathan et al., 2020).

Homogenous and heterogenous networks

Homogeneous and heterogeneous networks are two types of wireless networks used in telecommunication systems. A homogeneous network refers to a wireless network where all nodes, or base stations, have the same characteristics, such as transmitting power, and are used for the same purpose (Mhatre et al., 2004), as shown in Figure 2.1.

1

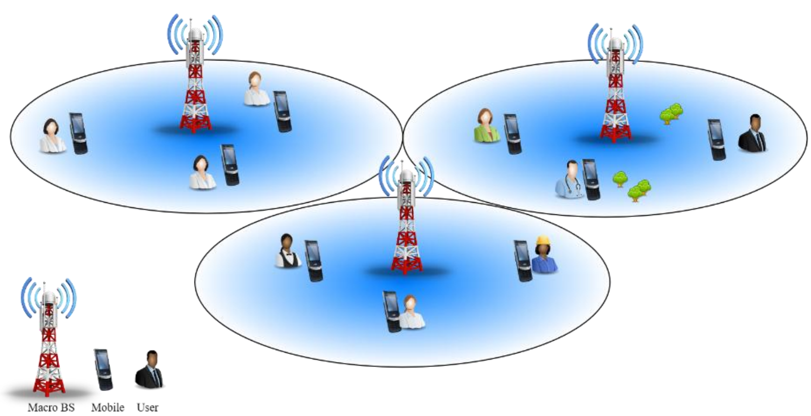

Figure 2.1: Homogenous network with similar types of base stations

In a homogeneous network, all nodes have similar coverage areas and transmit at the same power level. This type of network is typically used for providing coverage in a large area, such as a city or a region, with uniform wireless service. Homogeneous networks are often deployed using the same type of technology, such as 2G, 3G, or 4G. They are designed to handle high traffic volumes (Johansson & Klas, 2007).

On the other hand, in a heterogeneous network, nodes have a variety of characteristics and capabilities. These characteristics include different coverage areas, power levels, and technologies. This type of network is typically used to provide coverage in areas with varying demand levels. For example, densely populated urban areas or sparsely populated rural areas. Further, heterogeneous networks can also be employed to extend coverage in buildings. This is where different types of nodes are installed to extend coverage in different areas (Hossain et al., 2015). Heterogeneous networks often use small cells, such as femtocells or picocells, to ensure coverage in areas with high demand or poor signal strength. These small cells are connected to a larger macrocell, which provides coverage over a larger area. This type of network can improve coverage and capacity while reducing infrastructure deployment costs (Fogue et al., 2018). Figure 2.2 demonstrates this architecture.

2

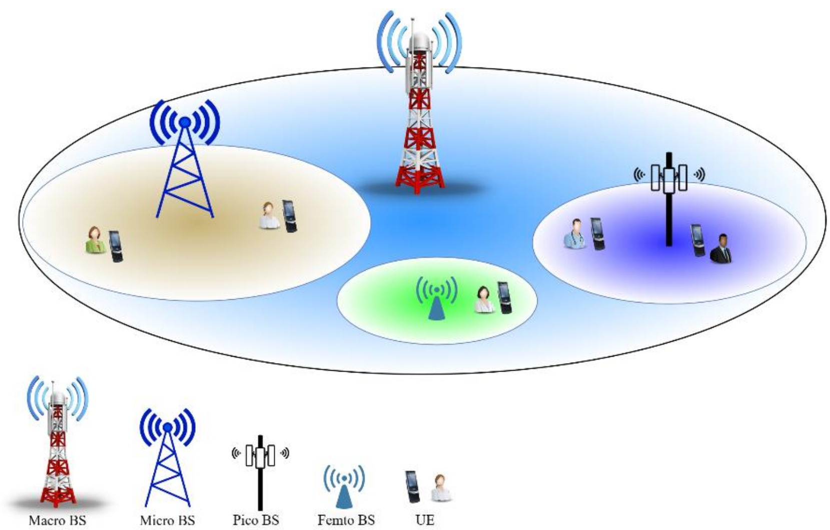

Figure 2.2: Homogenous network with different types of base stations

Overall, both homogeneous and heterogeneous networks are critical for providing wireless connectivity and supporting the increasing demand for high-speed data services and the emergence of new applications and services. The small BSs that reside within the coverage area of a heterogeneous network have shown that their low-powered radio communication equipment has provided a significant reduction in the total power consumption of the heterogeneous network (S. Mishra & C. S. R. Murthy, 2018). The use of low-power equipment in a heterogeneous network, in contrast to a homogeneous network, can effectively reduce the power footprint of the network by reducing the network's power consumption as a whole. Energy is being used and managed in an efficient manner, which can be regarded as a positive aspect (Hossain et al., 2022).

Base Station

Cellular base stations, often simply referred to as "base stations" or "cell towers," are fundamental components of cellular networks. These towers play a crucial role in facilitating wireless communication by serving as intermediaries between mobile devices (such as smartphones) and the core network infrastructure (Lehr et al., 2020). Key characteristics of cellular base stations are as follows:

1. **Signal Transmission and reception:** Base stations transmit and receive radio signals to and from mobile devices within their coverage area. When a mobile device initiates a call, sends a text message, or accesses data services, it communicates with the nearest base station.
2. **Coverage Area:** Each base station provides coverage to a specific geographic area referred to as a "cell." The size of a cell can vary, from a few meters in urban areas to several kilometres in rural regions. When a user moves within the network, their device seamlessly switches between different base stations to maintain connectivity.
3. **Frequency Bands:** Base stations operate on specific radio frequency bands allocated by regulatory authorities. Different frequency bands are used for voice and data communication, and they determine the range and capacity of a base station.
4. **Cellular Network Architecture:** Base stations are part of a larger network infrastructure that includes core network elements like switches, routers, and data centres. Together, these components enable communication between mobile devices, as well as connections to other networks, such as the internet.
5. **Multiple Antennas:** Modern base stations often employ Multiple-Input, Multiple-Output (MIMO) technology, with multiple antennas for both

transmission and reception. This enhances network performance, improves signal quality, and increases capacity.

6. **Backhaul Connections:** Base stations are connected to the core network via wired or wireless backhaul links. These connections enable data to flow between the base station and the central network infrastructure.
7. **Small Cells:** In densely populated urban areas, small cell base stations are deployed to augment coverage and capacity. These smaller base stations are often installed on streetlights, utility poles, or rooftops to enhance network performance in areas with high user density.
8. **Tower Infrastructure:** Base stations are typically installed on tall structures, such as cell towers or buildings, to ensure that their signals can cover a wide area. Tower maintenance and power supply are critical to the continuous operation of base stations.
9. **Security and Redundancy:** Base stations are designed with security measures to protect against unauthorized access and cyber threats. Additionally, redundancy measures are in place to ensure network reliability in case of equipment failures or natural disasters.

Cellular base stations are central to the operation of cellular networks, providing the backbone for mobile communication. Their strategic placement and efficient management are essential to delivering reliable and high-quality wireless services to users, and they play a pivotal role in the ongoing evolution of wireless technology, including the deployment of advanced networks like 5G (Qiao et al., 2015; Gao et al., 2018).

Type of Small Cell BS

There are several different types of wireless base stations, each with its own unique characteristics and applications. Here are some of the most common types of wireless base stations (H. S. Dhillon et al., 2011):

1. **Macrocell Base Stations**: Macrocell base stations are the most common type of wireless base station and are used to provide coverage over large areas, such as entire cities or regions. Macrocells typically have a range of several kilometers and use high-power transmitters to provide broad coverage (Arnold et al., 2010).
2. **Microcell Base Stations:** Microcell base stations are smaller than macrocells and are used to provide coverage in areas where there is high user density,

such as shopping malls, airports, and business districts (Ibrahim et al., 2020). Microcells typically have a range of a few hundred meters and use low-power transmitters to minimize interference with other cells.

3. **Picocell Base Stations:** Picocell base stations are even smaller than microcells and are used to provide coverage in very small areas, such as individual buildings or floors of buildings. Picocells typically have a range of less than 100 meters and use even lower-power transmitters than microcells (Huo et al., 2019).
4. **Femtocell Base Stations**: Femtocell base stations are the smallest type of base station and are designed to be used in homes and small businesses. Femtocells typically have a range of less than 10 meters and are used to provide coverage in areas with poor cellular coverage, such as rural areas or buildings with thick walls (Liu et al., 2018).

Voronoi Tessellation

Voronoi tessellation, also known as a Voronoi diagram or Voronoi partition, is a mathematical concept that divides a space into a set of regions based on the distance between a given set of objects (Okabe et al., 2009). In this tessellation, each point in space is assigned to a region. The region being defined as the set of all points that are closer to that point than to any other point in the given set. To create a Voronoi diagram, begin by selecting a set of points known as "sites." These points can be chosen randomly, but they are frequently chosen to represent some specific feature of the space being tessellated, such as the placement of BSs in a specific area. It is normal to use Voronoi tessellation to distribute users and BSs on a plane when the distance or transmit power between the BSs is not equal to the user's (K. Huang and J. G. Andrews, 2012).

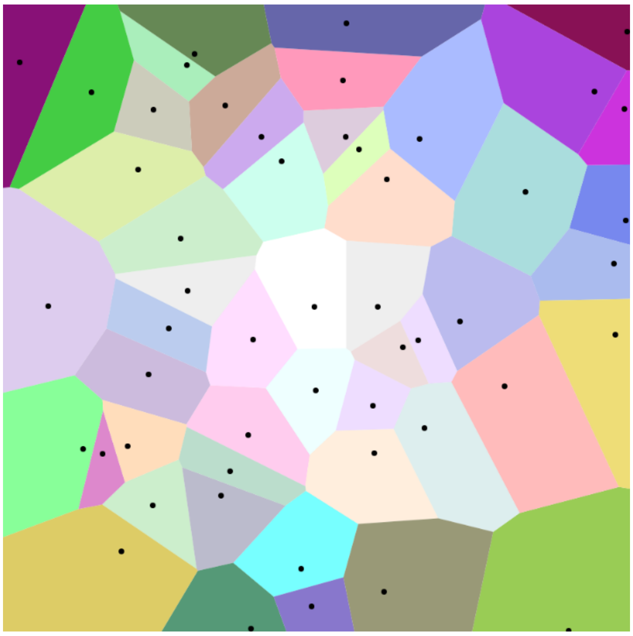

Figure 2.3: Voronoi Tessellation

The method can also be applied when different transmit powers are used over different tiers of the network (H. S. Dhillon et al., 2011). As for the rest of the BSs, which are not associated with a typical mobile user, they are considered to be interferers in the network. This can be used when calculating the strength of the signal that a mobile user receives from the nearest base station. It is called a serving BS because it is the BS that responds to the mobile device's requests. The location of the mobile users determines whether or not a BS can provide coverage to them (Ai et al., 2015). In Figure 2.3, the Voronoi tessellation partitioned BS is illustrated by dots indicating the locations of the BSs. They are divided into regions based on the strongest received signal strength (RSS), so a BS can serve when a mobile user moves within a region. Voronoi Tessellation used to simulate received signal strength (RSS) for user association in this study.

Control-Data Seperation Architecture (CDSA)

Traditional cellular systems raise some issues that can be addressed by logically separating the control and data planes (Ansari et al., 2019). CDSA as shown in Figure 2.4 is a concept based on the assumption that a wide coverage area can be provided by only a small amount of signalling and a small amount of data traffic, which is achieved by the use of its MCBs, which offer a constant and reliable coverage layer at low frequencies, while SCBs have a large footprint that allows them to provide robust connectivity and mobility in addition.

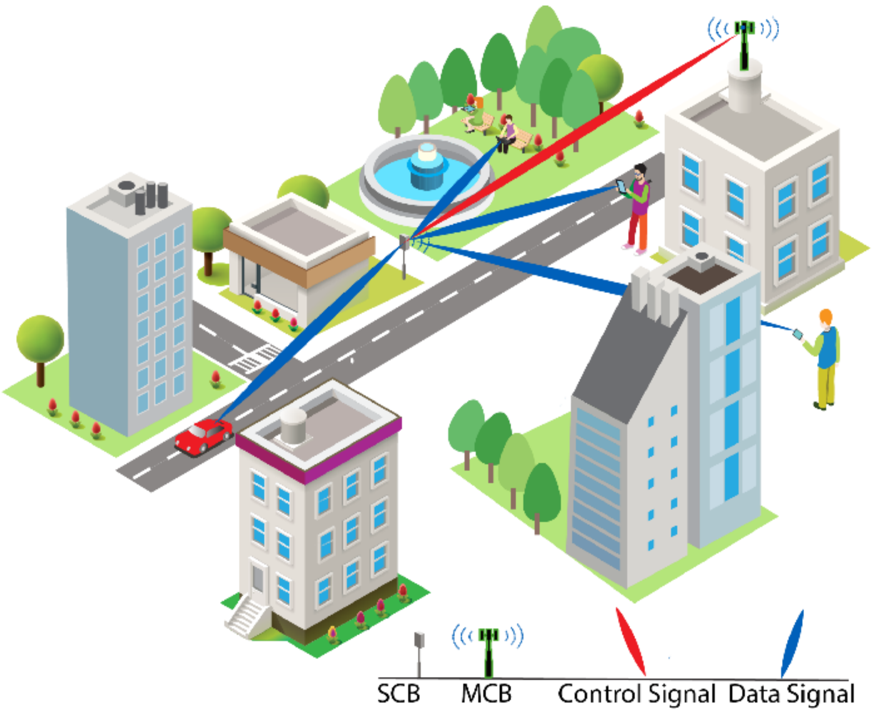

Figure 2.4: CDSA architecture

Therefore, in CDSA the MCBs are responsible for the entire network, including the SCBs that are under their coverage, as well as providing data traffic to the UEs based on their service demands, which is determined by their MCBs (Saha et al., 2017).

There is a key benefit of this application: supporting the control of network activities, especially when sending SCBs into sleep mode, off mode, or even just leaving them on, is therefore predicted to have a significant impact on energy efficiency. In addition to keeping users connected, the signalling network also consumes a negligible amount of energy in order to keep all users connected. The fact that this architecture was chosen for this study is one of the reasons for the choice of this architecture. The architecture was first introduced in the literature by (Capone et al., 2012). MCBs and SCBs may also be connected to one device at the same time. Moreover, another advantage of the CDSA design is that it is also effective in preventing coverage gaps that may occur when a large number of SCBs within a specific area turn off at the same time. Further, it provides highly available systems that can serve UEs even in the event that one or more elements of the system fail (Zhang et al., 2015). In comparison to legacy systems, the flexible nature of the SCB operation mode allows them to achieve EE up to four times higher than legacy systems. Further, the (30 GHz to 300 GHz) millimeter wave (mmWave) frequency band is also considered to be a viable candidate for meeting the new service demand and overcoming spectrum congestion that exists. However, conventional cellular networks are not designed to switch on and off frequently. While CDSA, as explained above, has all of the features necessary to perform dynamic on and off switching at a high level of agility, without hampering performance. It has also been demonstrated that CDSA can provide better SE due to the selection diversity that results from a large number of SCBs. Another feature of CDSA that can yield better SE than conventional networks is the possibility of centralized interference coordination (Mohamed et al., 2015). It is to our knowledge that few previous studies have involved EE and SE analysis for CDSA networks, to the best of our knowledge. The following are a few of the studies that investigate the feasibility of implementing the CDSA architecture in a variety of different research projects:

- Beyond Cellular Green Generation (**BCG2**).
- Toward Green 5G Mobile Networks (**5grEEn**).
- Millimetre-Wave Evolution for Backhaul and Access (**MiWEBA**).
- Mobile and wireless communications Enablers for the Twenty-twenty Information Society (**METIS**).

Although the functionality separation scheme is based on heterogeneous network architecture, it can also be applied directly to multicarrier systems with homogeneous coverage since it is based on heterogeneous network architecture. The primary carrier contains control and data signalling, while the secondary carriers are reserved for the pilot signal and UE-specific data signalling, according to LTE-A standards (Xu et al., 2013). Manually switching on/off the SCBs and controlling their beam directions would be impractical and not timely enough when traffic is rapidly changing. In most of these applications, CDSA can play a key role. Automating these techniques makes them more convenient and more effective, allowing for easier implementation and maximization. Such as self-optimization networks (SONs)-based mechanisms that allow the detection of short-term energy savings opportunities and the proper reconstruction of long-term energy efficiency improvement strategies (Mohamed, Abdelrahim, et al., 2015).

Energy Efficiency Strategies

The number of mobile subscriptions is expected to reach 8.9 billion by the end of the year, with 136 Exabytes of data traffic per month being driven by 5G cellular networks, with 25 percent of the traffic being provided by those networks. For the past 25 years, the peak download data rates for both Wi-Fi and cellular systems have increased exponentially (Dahal & Madhu Sudan, 2022). During the next few years, wireless networks will have to carry a greater amount of data. In the fifth generation (5G) of mobile networks, it is expected that mobile data will be transmitted 1000 times more than in the fourth generation (4G). As a result of the high demand for data traffic, heterogeneous networks (HetNets) consisting of different types of base stations (BSs) and multiple access points (MABs) in both indoor and outdoor regions have been developed and deployed in practice for the purpose of handling the high volume of data traffic (Ibrahim et al., 2017). Although SCBs consume a relatively low amount of power, the ultra-dense deployment of these devices will increase their energy consumption. It is estimated that 60% to 80% of the energy consumed by wireless mobile networks is sourced from BSs. According to mobile network operators, the estimated cost of their energy consumption accounts for around 30% of their operation expenditure (OPEX) (Andrae et al., 2015). In addition to that, BSs are also powered by the national power grid, which is the most reliable source of energy but also powers technologies which emit carbon dioxide ($CO2$). In terms of electricity consumption, the global cellular network consumes 60 TWh, which is the equivalent of three or four 2000 MW power plants. Nearly half of a cellular network's operating and maintenance costs are attributed to the energy expenditure of BSs (Alamu et al., 2020). $CO2$ is the major contributor to global warming, which is a result of greenhouse gas (GHG) emissions. Currently, the information and communication technology (ICT) industry is responsible for 4% of worldwide emissions of carbon dioxide, with estimates indicating that this figure will reach 5% by the year 2025, and up to 14% by the year 2040 . It is estimated that the wireless mobile network sector contributes between 15% and 20% of the $CO2$ emissions in the ICT industry (Kweku et al., 2018). Since BSs use a large amount of energy and emit a large amount of $CO2$, based on the aforementioned, the consideration of energy efficiency has gained traction in recent years as a result of their high energy consumption and significant contribution to the world's carbon footprint, and therefore, have become an important topic in the area of wireless communication systems. As a result, an integrated research strategy will be required in order to combine multiple cross-layer approaches and take advantage of their benefits in order to construct a more energy-efficient network. Several energy-efficient strategies have been developed, including on-off BS operation, network planning, resource allocation, and cell zooming (Sofi et al., 2018). According to the results, shutting down underused BSs can significantly increase EE. A comparison of the methods used to improve the EE can be seen in Table 2.1, where each method has its own advantages and disadvantages. In order to further optimize the EE of the two-tier network, many hybrid strategies have been proposed, which combine one or more techniques to further enhance the EE of the network. All of the SCB types such as micro, femto, macro, and pico are classified by their coverage area, the size of the cell, the power output, and the data rate associated with each cell (Bousia & Alexandra, 2016).

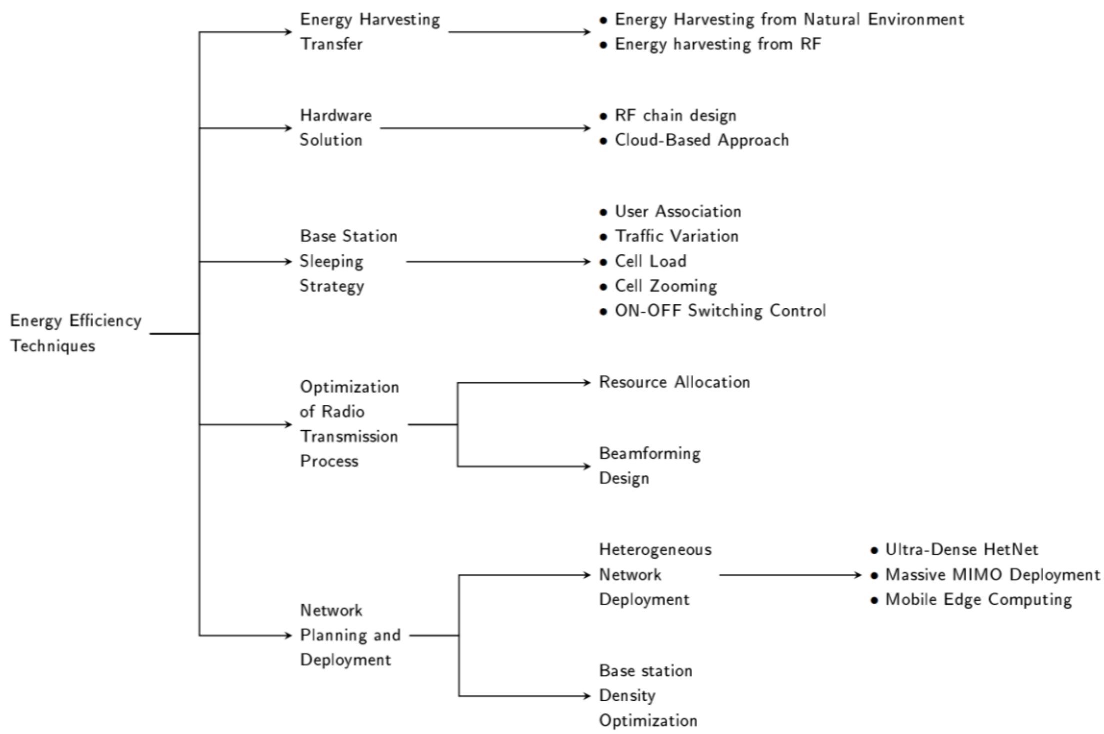

Figure 2.5: Various types of energy efficiency techniques

This study carry out the BS sleeping strategies. Table 2.1. summarizes and describes the benefits and drawbacks of the various recent studies on energy-optimization strategies for SCBs that have been conducted recently.

Table 2.1: Comparison for EE techniques at the BS level

Citation of the Study	Advantages of the Scheme	Disadvantages of the Scheme
(Wei Li et al., 2018)	The centralized algorithm used to obtain the optimal solution is based on Dinkelbach's method. In order to enhance EE and simplify calculations	The update of the global variables could fail and information sharing across BSs could be imprecise due to noise
(Rizvi et al., 2017)	The energy efficiency of the wireless network is increased by the strategic placement "rational manner" of SCBs	Only the power transmitted by BSs in the tier is taken into account for EE research
(Aligrudic et al., 2014)	The plan demonstrated that embracing heterogeneous architecture for wireless cellular networks can result in considerable gains in throughput and energy efficiency	The provided numerical and simulation results, presuming real urban environments, provide a strong foundation for future work in identifying the best HetNet topologies
(Bourast et al., 2017)	For densely deployed femto cells, an incentive-based sleeping mechanism, different sleep modes, and hybrid access schemes that enhance performance and EE	Throughput gains are based on user reallocation
(Beitemal et al., 2018)	The various patterns that only activate one of the three sectors are especially useful when using the sector-based switching technique. Making sure that interferer cells are as far away as feasible, enabling realistic interference modeling,	The scheme does not consider the downlink transmission EE

	minimizing coverage gaps, and improving user uplink transmission EE	
(Ryoo et al., 2018)	UE energy usage can be reduced by 18% for the entire device, including the display, and by 50% for the modem alone	The reduction in power consumption is limited to UE modems only
(Hajri et al., 2018)	The proposed clustering approach surpasses the scheme in which the most popular files are cached in all SCBs in terms of the impact of the various system parameters on the cache hit probability and EE	It is necessary to conduct further research on the ideal cache placement approach for diverse popularity profiles and mobility patterns
(Aydin et al., 2017)	The multi-objective optimization methodologies are used in the optimization framework created for both EE and SE maximization in a network where radio resources are shared among several operators	Systems that are limited by interference as well as noise can use this method
(Yang et al., 2017)	When compared to non-cooperative or non-harvesting systems, the optimization technique of joint BS-Sw and power allocation yields about 15–20% higher EE. The proposed distance-based BS-Sw method	There is a coverage hole, therefore methods such as cell zooming must be used; this is left for future work

Signal-to-interference-plus-noise Ratio

Wireless communication systems have become an integral part of modern society. They are used in a wide range of applications, including mobile phones, Wi-Fi, and satellite communication. In wireless communication, the quality of the received signal is affected by various factors such as interference, noise, and fading (Vlavianos et al., 2008). Therefore, it is important to have a metric that can measure the quality of the received signal, which is where the signal-to-interference-plus-noise ratio ($SINR$) comes in. $SINR$ is an essential metric for assessing the performance of wireless communication systems. It is defined as the ratio of the signal power, P , to the sum of interference, I, plus noise power, N_0, and is used to determine the maximum achievable data rate and the range of the communication system. It is also a key concept in defining how mobile devices receive signal information. In the process of propagating from a transmitter to a receiver, the transmitted signal is attenuated due to fading, path loss, and shadowing (Sehgal et al., 2020). It is also used for power control and resource allocation in the wireless communication system and to evaluate the capacity and quality of service (QoS). Thus, $SINR$ can be calculated by dividing the received signal power, P, by the sum of interference, I, and noise power, N_0, as follows:

$$SINR = \frac{P}{I + N_0} \tag{2.1}$$

The interference, I, is the power of other signals that are present in the same frequency band, and the noise power, N_0, is the power of the random electrical signals that are present in the receiver. $SINR$ can be expressed in decibels (dB) using the following formula:

$$SINR(dB) = 10 \times log_{10} \frac{P}{I + N_0} \tag{2.2}$$

Using a channel model with attenuated signals, the $SINR$ can be expressed as follows:

$$SINR = \frac{Phd^{-\alpha}}{I + N_0} \quad (2.3)$$

Where h, is the fading of the channel, d, is the distance between transmitter and receiver, and α, is the path loss exponent parameter, which is assumed to be greater than two for urban areas. The classification of this metric is provided by Table 2.2 (Razali et al., 2017).

Table 2.2: Classification of Path loss exponent

Environment	**Path loss exponent**
Free space	2
Urban area	2.7 – 3.5
Suburban area	3 – 5
Indoor line-of-sight	1.6 – 1.8
Obstructed in building	4 – 6
Obstructed in factories	2 - 3

In accordance with the category of the BSs, the transmit power of the BSs falls within the minimum and maximum thresholds for transmit power that can be transmitted, the maximum transmit power of a macro BS, for example, is 20 Watts. For small BSs, however, the maximum transmit power depends on their category, like micro BSs, which offer a maximum of 6.3 watts, pico BSs, which offer a maximum of 0.13 watts, and femto BSs, which offer a maximum of 0.05 watts (Auer et al., 2011). Some metrics considered in this study that relate to $SINR$ include:

Power Control: In systems where users interfere with each other, power control is used to prevent interference between users. All users' transmit power is adjusted to meet a threshold for acceptable performance by adjusting their $SINR$; users may have different thresholds, depending on their needs (Elbatt et al., 2004).

Received Signa Strength (RSS): RRS is a measure of power level of the signal received by a wireless device from a wireless access point or transmitter. It is usually measured in decibels (dBm) and represents the amount of power present in the received signal. It is affected by various factors such as the distance between the transmitter and the receiver, the number of obstacles in the signal path, the frequency of the signal, and the sensitivity of the receiver. The RSS is also affected by interference from other wireless devices operating in the same frequency band. The RSS is an important metric in wireless communication systems as it can be used to determine the quality of the wireless signal and to adjust the power level of the transmitter to optimize the signal strength (Liu et al., 2020). In this study, the Received Signal Strength Indicator ($RSSI$) used to estimate the distance between the transmitter and the receiver, and to locate the position of the receiver in a two-tier wireless network.

However there are many factors along the path from a transmitter to a receiver that contribute to the total received power at a mobile device being less than the total transmitted power. A path loss, P_L, is measured by dividing the transmit power, , P_t, by the received power, P_r, and can be calculated as follows:

$$P_L = \frac{P_t}{P_r} \tag{2.4}$$

Shadowing or attenuation, is a phenomenon that occurs in wireless communication systems where the signal strength is reduced due to obstructions in the signal path. These obstructions can be physical objects such as buildings, trees, or terrain, or they can be caused by atmospheric conditions such as rain, fog, or snow. When a wireless signal encounters an obstruction, it may be absorbed, reflected, or scattered, causing the signal strength to be weakened at the receiver. This effect is more pronounced at higher frequencies and over longer distances. The amount of shadowing depends on the distance between the transmitter and receiver, the frequency of the signal, the size and shape of the obstruction, and the characteristics of the wireless environment (Naseem et al., 2018). To reduce the impact of shadowing on wireless communication by using techniques such as diversity, which involves using multiple antennas to improve the quality of the signal, and power control, which involves adjusting the power level of the transmitter to optimize signal strength. Other techniques, such as beamforming, channel equalization, and error correction, can also be used to improve the quality of the wireless signal in environments with high levels of shadowing (Shankar & P. Mohana, 2017).

Bias function value

In research studies, a bias function value may be used to adjust a certain values to account for factors that impact the results. For example, a study examining the effectiveness of a new medication for treating a particular condition may include a bias function to account for variables that may influence the outcome, such as age, gender, and overall health status of the participants. The bias factor is used to adjust the results of the study to better account for these variables and increase the accuracy and generalizability of the findings. (Accorsi et al., 2021) used common biases to assist in the evaluation of a continually expanding body of literature on COVID-19.

The bias function value is typically determined through statistical analysis and modelling of the data collected in the study. The value of the bias function value is based on a range of factors, including the size of the study, the nature of the variables being adjusted, and the statistical methods used. The bias function also may account as a multiplier that is used to adjust a particular value, such as base station power consumption, to account for factors that may not have been explicitly modelled or accounted for in the original calculation (Geffers et al., 2022). In the context of base station power consumption, the bias function can be used to account for various factors that may affect power consumption, such as climate, terrain, usage patterns, and equipment differences. For example, a base station located in a hot and humid environment may consume more power than a similar base station located in a cooler climate, and the bias factor can be used to adjust for this difference. The goal of (Sun et al., 2019) was to improve network EE by considering three important factors: cell range expansion bias, the power of an almost blank subframe, and the density of SCBs. The value of the bias function is typically determined through empirical testing and validation, where actual power consumption data is collected from a range of base stations operating in different environments and usage scenarios. This data is then used to determine the relationship between the various factors that affect power consumption and the actual power consumption value. Based on the above-mentioned benefits, using the bias function value can be useful for optimizing power consumption and improving the overall efficiency of the base station network. Thus, the bias function value was used in our study to adjust the power consumption of SCBs.

Swarm Intelligence (SI)

SI is a field of study that deals with the collective behaviour of decentralized, self-organized systems, typically composed of large numbers of simple individuals or agents (Sadiku et al., 2021). Swarm Intelligence is inspired by the behaviour of social animals such as ants, bees, birds, and fish, and aims to develop algorithms and methods that can simulate and exploit the emergent properties of such systems. One of the main branches of Swarm Intelligence is Swarm Optimization, which aims to solve optimization problems by using a population of solutions that interact and exchange information to find better solutions (Schranz et al., 2021).

One of the most famous algorithms in Swarm Intelligence is the Ant Colony Optimization (ACO) algorithm, which is inspired by the foraging behaviour of ants. In ACO, artificial ants move in a simulated environment, laying pheromone trails to mark the paths they have explored. Other ants can then follow these trails, reinforcing them if they find a good solution, or abandoning them if they find a bad one. By using this simple mechanism of positive feedback, ACO can efficiently search for the optimal solution in complex optimization problems (Miao et al., 2021). Other algorithms in SI include Particle Swarm Optimization (PSO), which simulates the flocking behaviour of birds, and Artificial Bee Colony (ABC), which models the foraging behaviour of honeybees (Santhi, G. & E. Gowri, 2017). In addition, the GOA that focused on in this study is inspired by the collective behaviour of grasshoppers, where the grasshoppers communicate with each other to locate the best food sources. The algorithm uses a decentralized population of grasshopper agents to explore the search space and find the optimal solution to a given problem. The grasshoppers move towards better solutions based on their position and the information they share with their neighbours, creating an emergent behaviour that leads to global optimization. Swarm intelligence algorithms, such as GOA, are characterized by their ability to adapt to changing environments, their robustness against noise and uncertainty, and their ability to find optimal or near-optimal solutions in complex and dynamic problems (Saremi et al., 2020). SI is a promising approach to solving complex problems in various fields, including optimization. Its ability to exploit the emergent properties of large-scale systems makes it particularly useful for solving problems that traditional algorithms find challenging or hard to solve.

As a designer, on the other hand, you need to be able to articulate challenges through meta-heuristics in order to face these challenges. Furthermore, deterministic optimization approaches and search procedures are inefficient when dealing with nonlinear programming (NP)-hard problems such as the one dealt with in the current study where the problem is nonlinear programming (NP). There is a possibility of finding near-optimal solutions to NP-complex problems by using stochastic optimization methods (T. Dalia et al., 2022). According to (D. Ashraf 2018), the process of optimization refers to the selection of the most appropriate values for the variables of an objective function, i.e., EE in our case, that minimizes or maximizes that objective function. Recently, a variety of research initiatives have been focused on nature-inspired computing, and a lot of attention has been paid to population-based algorithms, which are one of the most common stochastic optimization approaches (Schranz et al., 2021). The use of optimization algorithms can also be considered as a new approach to developing new techniques based on the concepts and inspiration of natural biological evolution in order to create new techniques. Our work involves the use of optimization techniques in order to select the appropriate mode of operation for each SCB in order to maximize the EE across the whole two-tier network as a result.

The Grasshopper Optimization Algorithm (GOA)

GOA is a metaheuristic optimization algorithm that is inspired by the swarming behaviour of grasshoppers. The algorithm was first introduced by (S. Mirjalili et al., 2018) as a new approach to solving optimization problems. The GOA algorithm mimics the behaviour of grasshoppers in their search for food sources, which involves three main stages: searching, congregating, and dispersing as explained in Figure 2.6.

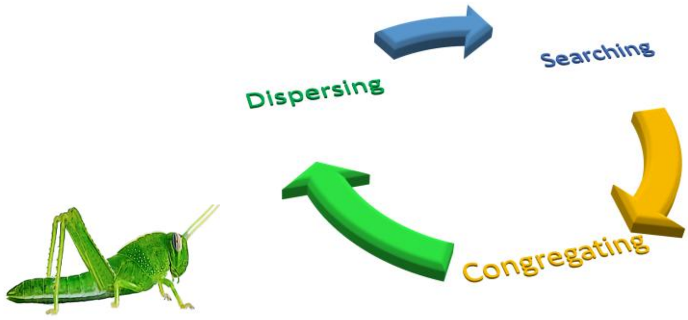

Figure 2.6: The main search stages of Grasshopper

In the searching stage, individual grasshoppers explore the environment by jumping randomly. In the congregating stage, grasshoppers interact with each other and share information about the location of food sources, and in the dispersing stage, the grasshoppers move away from the food sources to avoid overcrowding and competition. The GOA algorithm models this behaviour by using a population of grasshoppers that move in the search space to find the optimal solution. In each iteration, the algorithm updates the positions of the grasshoppers based on their fitness values and the information they share with each other. The fitness of each grasshopper is calculated based on the objective function of the optimization problem, and the algorithm tries to minimize or maximize it based on the problem type.

The GOA algorithm has been shown to be effective in solving a wide range of optimization problems, including function optimization, feature selection, and parameter tuning. The algorithm is relatively simple to implement and has a small number of parameters to adjust, making it suitable for both researchers and practitioners. As an added benefit, it demonstrated a high rate of convergence through high exploration levels, which in turn leads to an adaptive mechanism capable of smoothly balancing exploration and exploitation (S. Z. Mirjalili et al., 2018). This makes the GOA algorithm capable of handling single and multi-objective problems and outperforming other techniques because of these qualities. In this study, the GOA algorithm is used to optimize the EE. A cooperative GOA-based Variant Power Mode Selection (VPMS) algorithm is proposed to select the appropriate power mode for each SCB and calculate the EE for two-tier networks. Grasshopper movement is modelled mathematically using the following equations:

$$X_i = S_i + G_i + A_i \tag{2.5}$$

$$S_i = \sum_{\substack{j=1 \\ j \neq i}}^{N} s(d_{ij})\, \widehat{d_{ij}} \tag{2.6}$$

$$S(r) = f\, e^{-\frac{r}{l}} - e^{-r} \tag{2.7}$$

$$G_i = -g\widehat{e_g} \tag{2.8}$$

$$A_i = u\widehat{e_w} \tag{2.9}$$

Where X_i, S_i, G_i and G_i, are the grasshopper position, social interaction forces, gravitational force, and wind advection, respectively. d_{ij}, and $\widehat{d_{ij}}$, are the distance and unit vector from the i^{th} to the j^{th} grasshopper, respectively, $S(r)$, refers to the social force that exists between two grasshoppers, where, f, indicates the intensity of attraction and, l, is the attractive length scale. g, is the gravitational constant and , $\widehat{e_g}$, denotes the unity vector toward the centre of the earth, u, is a constant drift and, $\widehat{e_w}$, is a unity vector in the direction of the wind.

The following is a modified version of the equation for solving optimization problems.

$$X_i^d = c\left(\sum_{\substack{i=1 \\ j \neq j}}^{N} c\frac{ub_d - lb_d}{2} s\left(|x_j^d - x_i^d|\right) \frac{x_j - x_i}{d_{ij}}\right) + \widehat{T_d} \tag{2.10}$$

Where, lb_d, and, ub_d, are the lower and upper bounds in the, d^{th}, dimension, respectively, $\widehat{T_d}$, is the value of the d^{th} dimension in the target (best solution discovered so far), and, c, is a decreasing coefficient to shrink the comfort, repulsion and attraction area. Parameter, c, is updated using the formula below.

$$c = c_{max} - i \frac{c_{max} - c_{min}}{L} \tag{2.11}$$

Where, c_{max}, is the maximum value , c_{min}, is the minimum value, i, is the index for the current iteration, and, L, is the maximum number of iterations.

However, like other metaheuristic optimization algorithms, the performance of GOA depends on several factors such as the choice of parameters, the problem complexity, and the problem type (Aljarah et al., 2018). Therefore, it is important to carefully tune the parameters of the algorithm to achieve the best results.

Related works

There is a significant amount of research on improving energy efficiency in wireless heterogeneous networks (HetNets). There has been previous research such as (Xiao et al., 2016) that has discussed the improvement of both EE and coverage for multi-tier HetNets, which are made up of MCBs and other types of SCBs, such as picocells and femtocells, among other components. It was proposed that an EE optimization problem would be formulated taking into consideration the throughput performance and the fairness of resource allocation. It has been shown that the deployment density of SCBs has a significant impact on the EE and coverage performance of SCB networks using stochastic geometry tools and the Poison point process (PPP) distribution used in the simulation. The performance of downlink transmissions in a vehicle network has been compared by (Patra et al., 2016; Mao et al., 2015) in two scenarios, one with MCBs but not SCBs and the other with MCBs and SCBs. This technique was shown to improve the average end-to-end delay, the throughput, the EE, and the average EE of all packets within a network. It was observed in a paper by (Peng et al., 2015) that small cell networks were modelled as homogeneous Poisson point processes, in which power control strategies of all-on and all-off were employed to determine the average feasible cell rate. In order to optimize the energy consumption of HetNet, (Ahmed et al., 2021) proposed an energy use optimization scheme that was centralized by the MCB and which included several micro-cell BSs and wind turbines (renewable energy sources) to improve the energy usage optimization scheme. In this study, the optimization problem was formulated as a mixed integer nonlinear programming problem and solved using the interior point method as a means of solving the problem. Different sizes of HetNet were found to provide significant energy savings when compared to HetNets of similar sizes. Similarly, another study (Chung & Y.L., 2015) suggested that small cells could be switched on and off, zoomed in and out, depending on location, speed, and traffic load variations in order to meet UE QoS requirements. A distributed game theory was applied by (Antonopoulos et al., 2015) to reduce energy consumption. This scenario will result in the switch off of the mobile network operators' base stations if their subscribers are covered by a different mobile network operator. It was also proposed by (Oikonomakou et al., 2015) to apply a cooperative switching off mechanism for both MCBs and SCBs to ensure UE QoS during low-traffic hours. Cooperative HetNets were fed by hybrid sources of energy via combined BS switching and power allocation using combinatorial optimization to solve the EE maximizing problem (Euttamarajah et al., 2021). As a result of its two dynamic thresholds, the proposed algorithm is tune-free, and performs 15% to 20% better than non-harvesting and non-cooperative algorithms. A suboptimal distance-based BS switching scheme was used to solve the power allocation problem with Lagrange dual decomposition. Although turning off BSs results in significant energy savings, it contributes to significant delays in UE traffic response times. It is because BSs must be activated from the off state before they can serve clients. To reduce energy consumption and eliminate the long delay problem associated with a deactivated BS, most of its elements are turned off and it enters sleep mode. By responding quickly to requests, it does not have to enter the off mode as quickly. Cellular networks are currently implementing several power-saving measures, including sleep modes for BSs (Arshad et al., 2012; Li, Y. et al., 2013). A number of energy saving strategies for femtocell base stations and user equipment (UEs) were proposed in (IEEE 802.16m, 2011) including low duty operation mode and sleep mode respectively. The IEEE 802.11b standard introduced sleep mode in place of the traditional on-off mode as an effective way to reduce small cell energy consumption. The researchers found that sleep mode consumes 10% of the total energy, while switched-off mode consumes almost no energy at all (F.H. Panahi et al., 2019). A total of three sleep strategies were investigated (Ashraf et al., 2011; F. Boccardi, 2011) which were controlled by SCBs, UEs, and the core network, respectively. Securing these strategies was found to reduce energy consumption in the network by 13-56%. It has been demonstrated that active-aware sleep strategies for MCBs and femtocells in a two-tier network have been adapted in (Wang et al., 2015) in order to investigate the impact of EE utilizing stochastic geometry to develop energy savings with a consideration for coverage extension. EE and coverage probabilities were shown to be significantly influenced by sleeping schemes based on the numerical results. The use of multiple sleep levels was further explored in (Vereecken et al., 2012) which suggested four different modes of sleep in a femto-cell network for reducing power consumption and improving wake-up time. A semi-sleep mode is an access scheme proposed by (Zhang et al., 2016) which takes into account user-demanded service and fairness. Under certain constraints, the network EE improved by 54%. In order to save energy and reduce drop rates, (El Amine et al., 2022) developed a multilevel sleep mode for SCBs in a heterogeneous network architecture. SCBs can adapt their activities according to service delay constraints using reinforcement learning. With a drop rate of about 5%, significant energy savings can be achieved.

BSs were further reduced in energy consumption with the use of the CDSA architecture concept in HetNet (Ishii et al., 2012; Astely et al., 2012). (Mohamed, et al., 2015) demonstrates that improving analytical models for evaluating the signalling generated in CDSA networks and conventionally deployed networks during different handover scenarios can result in reduced overheads on HO signalling, and the MCBs are able to determine the operation mode of each SCB under their control by acting as centralized coordinators. By using it, (Ansari et al., 2019) realized significant energy savings and offered a re-configurable approach to network adaptation. Comparing a conventional cellular network with only MCBs to the separation architecture, the numerical results showed a reduction of 50% or more in energy consumption. Further, a modified separation architecture was studied (Kang et al., 2014), in which MCBs managed low-rate data traffic while SCBs controlled high-rate data traffic. The study presented a method for determining the states of BSs based on how many UEs request high-speed data traffic and how many UEs are located in areas where the regarded BSs and their neighbours' coverage overlap. The PSO algorithm was used to optimize a modified separated network architecture, and the numerical results showed that the suggested energy-saving plan provided a higher EE than traditional energy-saving methods. (Liu et al., 2016) found that CDSA can overcome overhead problems more efficiently than traditional cellular networks, especially when handling large bursts of traffic, such as Internet of Things traffic. To solve the optimization problem under the overall capacity constraint of a wireless system, a modified power consumption model and the Lagrangian dual decomposition method were presented. In simulations, CDSA networks showed a 14% EE gain over conventional networks. It was anticipated that CDSA would be a strong candidate for 5G networks (Wang et al., 2014; Taufique et al., 2019).

Among the factors considered by (Sun et al., 2019) in improving network EE were cell range expansion bias, the power of an almost blank subframe, and the density of SCBs. To determine the bias of cell range expansion and the power reduction factor, a linear search algorithm was used. While the proposed heuristic algorithm incurs low computational complexity, the simulation demonstrated a significant improvement in network efficiency. (Kudo et al., 2013) used Q-learning to learn the direct bias value for each UE, whereas (Lee et al., 2020) used HetNet BS to learn bias values. (Chou et al., 2015) introduced a load-based cell association scheme in which individual traffic loads of MCBs were used to determine the time and quantity of offloading. As a result of the implementation of a bias function (Abbas et al., 2017), small cells were effectively used by redirecting users from overloaded macro cells to underloaded small cells, thus balancing the two-tier network load. The Q-learning algorithm was used by (Kudo et al., 2013) for determining each UE's bias value in HetNet to extend pico-cell range. As has been widely discussed in the literature, the bias function also employed to determine the SCB's operation modes.

In the literature, the GOA algorithm has been used to solve several optimization problems; for instance, it has been used (Kurdi et al., 2018) to reduce cloud computing energy usage. According to (Ullah et al., 2019)’s simulations of consumer electricity bills, the GOA algorithm is capable of reducing consumer electricity bills by over 34.69%, in accordance with their simulation results. In comparison to other algorithms, the algorithm performed significantly better. (Wenhan et al., 2019) employed the recently updated version of the GOA algorithm to find the most energy-efficient solution to the optimal chiller loading problem. Accordingly, the GOA algorithm can be used for solving problems that have a variety of parameters in order to find an optimal solution, and using it in this study would contribute to obtaining the optimal bias function values for controlling the power consumption of each operating mode as well as finding the optimal bias function values for solving the problem in this study. An optimization routing method developed by (Sing et al.,

2019) is based on the nature-inspired GOA algorithm and is capable of improving energy consumption on sensor networks while maintaining a high level of QoS. There are several QoS criteria like packet loss, delay time, and throughput that are used to evaluate the performance of the suggested routing scheme, as well as residual energy. According to the study results, the technique offered a more energy-efficient network that had less time delay, less packet loss, and higher throughput than other methods. Although (Baidowi et al., 2021) manipulated two-tier networks using the GA algorithm to maximise energy efficiency, to the best of our knowledge, no prior study has manipulated two-tier networks using the GOA algorithm to maximize energy efficiency.

CHAPTER III

Methodology

In this chapter a novel mechanism for selecting an appropriate operation mode for each SCB is presented. By employing a bias function to manage the power consumption of each operation mode, each SCB has four power mode selections: on, standby, sleep, and off. Under a set of parameters, a Grasshopper Optimization Algorithm-based Variant Power Mode Selection (GOA-VPMS) is presented to maximize the energy efficiency of the two-tier network.

This chapter provides the system model, channel model, mechanism of classification, expression of signal-to-interference-plus-noise ratio (SINR), achievable data rate, calculation of power consumption, and calculation of energy efficiency. The problem statement and solution are described, and then, at the end, the performance and evaluation are provided.

System Model

The system model in this study contents a two-tier network with a single MCB and numerous SCBs, where the MCB is located at the origin, and the group of SCBs, S, and user equipment (UE's) ,U ,follow an independent Poisson point process distribution (PPP). All the necessary information regarding the UEs and SCBs is contained in the MCB, such as the RSS of each UE, the $SINR$ of each communication link, as well as the respective locations of the UEs and SCBs. The MCB will manage and assign each UE according to its RSS value to the appropriate UE based on its RSS value. Table 3.1 present the simulation network parameters.

Table 3.1: Simulation network parameters

Simulation Parameter	Value	Unit	
Number of MCB	1	-	
Number of SCBs, $\boldsymbol{S}$	50	-	
Number of UEs, $\boldsymbol{U}$	200	-	
SCB radius	<100	m	

$\boldsymbol{P_m^s}$	130	watt	
$\boldsymbol{P_s^s}$	4.8	watt	
$\boldsymbol{p_m}$	20	watt	
$\boldsymbol{p_s}$	0.75	watt	
$\boldsymbol{B}$	100	MHz	
$\boldsymbol{r_{in}}$	500	m	
$\boldsymbol{D}$	30	km	
Number of Iterations	100	-	
Upper bound $\boldsymbol{ub_d}$	100	-	
Lower bound $\boldsymbol{lb_d}$	-100	-	

Channel Model

The SCBs have different transmission powers, and for that reason, Voronoi tessellation is used to partition as illustrated in Figure 2.3. Our assumptions are that at the start of the simulation, the transmission power of the MCBs, P_m, and SCBs, P_s, will be set to their maximum value at the beginning of the simulation, while the algorithm proposed will then modify the transmission power accordingly. It is assumed that there already exists a Rayleigh fading channel between each of the u UEs and the associated s SCB, i.e., $h \sim exp(1)$ where, h_{su}, $s,$ the small scale fading coefficient (SSF) of the channel. The path loss exponent parameter, α, is assumed to be greater than 2 in this study, and the distance between, u, UE and its associated, s, SCB donated as, d_{su}, thus the received signal strength indicator ($RSSI$) is calculated as follows:

$$RSSI = \frac{P_s}{h_{su}{d_{su}}^{-\alpha}} \tag{3.1}$$

Signal-to-Interference-Plus-Noise Ratio (SINR)

In this scenario, the communication link between UEs that is served by a particular SCB only experiences interference from another SCB, since other SCBs have a different bandwidth in the CDSA scheme than MCB, so there is only one source of interference. Using this description, the received power at a given user can be described as, $h_{su}{d_{su}}^{-\alpha}$, and thus, $SINR_{su}$, can be calculated using this formula:

$$SINR_{su} = \frac{P_s\, h_{su}{d_{su}}^{-\alpha}}{\sum_{i\in S} P_s\, h_{su}{d_{su}}^{-\alpha} + N_0} \tag{3.2}$$

Where, N_0, is additive white Gaussian noise (AWGN) with a normalized value of 1.

Achievable Data Rate

For each communication link between one or more UEs that are served by a particular SCB, the achievable data rate is defined as follows:

$$R_{su} = W_{su} log_2\big(1 + (\Phi_{su}.SINR_{su})\big), \qquad \forall\, s \in S, u \in U \tag{3.3}$$

Where, W_{su}, represents the frequency bandwidth of each, s, SCB and, u, UE's link, while, Φ_{su}, is the Index variable of user association. Each mobile user presumed on the network receives an equal share of the network's bandwidth. As a result, each communication's bandwidth, W_{su}, can be expressed as, B/U, where ,B , is the system's bandwidth. In this study there is no data rate assumed between UEs and sets of SCBs (S_{sby}, S_{slp} and S_{of}) in Standby, Sleep, and Off operation modes which is different from (Baidowi et al., 2021). Therefore, the total data rate achieved by UEs that are active and associated with SCBs that are only in (On) operating mode (e.i. S_{on}) is described as follows:

$$R_{total} = \left[\xi_{on}^{s} \sum_{s\in s_{on}} \sum_{u\in U} R_{su}\right] \tag{3.4}$$

Calculation of Power Consumption

The SCBs will be classified into four groups based on the modes of operation they are operating in: On, Standby, Sleep, and Off, as it will be explained in more details later. Based on the number of SCBs in each group and on the mode of operation of each SCB, each group consumes a different amount of energy. Therefore, it is estimated that SCBs will consume the amount of power shown by Equation (17).

$$P_s^t = \left[\sum_{s\in S_{on}} (P_s^s + p_s) \times \Phi_{su}\right] + \left[\sum_{s\in S_{sby}} (P_s^s + p_s) \times 0.5 \times \Phi_{su}\right] + \left[\sum_{s\in S_{slp}} (P_s^s + p_s) \times 0.15 \times \Phi_{su}\right] + \left[\sum_{s\in S_{of}} (P_s^s + p_s) \times 0 \times \Phi_{su}\right] \quad (3.5)$$

In the following. Here are the results for the four modes of operation of the SCBs after applying the bias function:

$$P_s^{t^*} = \left[\xi_{on}^s \sum_{s\in S_{on}} (P_s^s + p_s) \times \Phi_{su}\right] + \left[\xi_{sby}^s \sum_{s\in S_{sby}} (P_s^s + p_s) \times 0.5 \times \Phi_{su}\right] + \left[\xi_{slp}^s \sum_{s\in S_{slp}} (P_s^s + p_s) \times 0.15 \times \Phi_{su}\right] + \left[\xi_{of}^s \sum_{s\in S_{of}} (P_s^s + p_s) \times 0 \times \Phi_{su}\right] \quad (3.6)$$

As can be seen from Equation (17), the inactive SCBs in off operation mode consume nearly zero power; therefore, their related bias function value ξ_{of}^s in the rest of this research ignored. On the other hand, MCB is always in active operation mode. As a consequence, the MCB's total power consumption is expressed as follows:

$$P_m^t = (P_m^s + p_m) \quad (3.7)$$

Where, P_m^s, and, p_m, donate the static power consumption and transmission power of MCB, respectively. Then, the reduced power consumed by MCB after applying the bias function value can be calculated as follows:

$$P_m^{t^*} = \xi_{on}^m \times (P_m^s + p_m) \quad (3.8)$$

Note: S_{on}, S_{sby} S_{slp} and S_{of} indicate groups of SCBs for On, Standby, Sleep, and Off, respectively. Therefore each operation mode's power consumption is adjusted by the bias function of the MCB and each set of SCBs (ξ_{on}^{m}, ξ_{on}^{s}, ξ_{sby}^{s}, and ξ_{slp}^{s}) separately. An overall two-tier network's power consumption is shown as follows:

$$P_{m,s}^{t} = P_{m}^{t^*} + P_{s}^{t^*} \tag{3.9}$$

Calculation of Spectral Efficiency

Spectral efficiency (SE) is a measure of the efficiency of a wireless communication system in utilizing the available frequency spectrum, the spectral efficiency of the system calculated as the total maximum data rate divided by the total available bandwidth as following:

$$Spectral\ Efficiency = \frac{Total\ achievable\ data\ rate}{Total\ Available\ bandwidth} \tag{3.10}$$

Therefore the Spectral efficiency (SE) for this scenario is calculated as follows:

$$SE_{HetNet} = \frac{R_{total}}{B} \tag{3.11}$$

Calculation of Energy Efficiency

Our work focuses on energy-efficient communication. In a heterogeneous network, energy efficiency is defined as the average rate of macro cells and small cells divided by the total power consumption of macro cells and small cells (23).

$$EE_{HetNet} = \frac{Average\ Rate_{HetNet}}{Average\ Power_{total}} \tag{3.12}$$

Therefore, the two-tier network's Energy Efficiency (ηEE) can be formulated as the ratio of the total achievable data rate of active SCBs to the total power consumption of the MCB and SCBs; therefore, from (15) and (20), the equation can be presented as:

$$\eta EE = \frac{R_{total}}{P_{m,s}^{t}} \tag{3.13}$$

It was determined in this study that the overall two-tier EE was measured in bits per joule for the two tiers network.

The Mechanism of Classification

In this study, MCB uses the ranking method to determine which operation mode is appropriate for each SCB in terms of this study's objective. First categorize the received signal in order to determine whether it can be associated with users based on its strength, from the strongest to the weakest. In order to distinguish between the first, second, and third strongest RSS's, the rank is then labelled 1 (On mode), 2 (Standby mode), and 3 (Sleep mode), and 4 (Off mode) for the remainder. For simplicity, Figure 3.1 and Table 3.1 explain this mechanism with an example of 6 SCBs and 3 UEs.

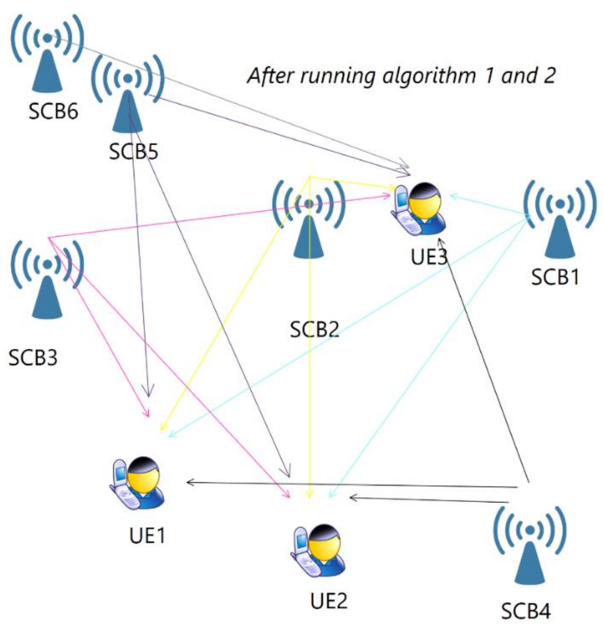

Figure 3.1: Mechanism of classification with 6 SCBs and 3 UEs

UE1 RSS	UE2 RSS	UE3 RSS		Associate UE with highest RSS
40dBm (SCB3)	50dBm (SCB3)	45dBm (SCB1)	1	ON Associate u with SCB
30dBm (SCB1)	40 dBm (SCB2)	35dBm (SCB2)	2	Inactive Mode
20 dBm (SCB4)	30 dBm (SCB1)	33dBm (SCB5)	3	
10 dBm (SCB2)	20 dBm (SCB4)	24dBm (SCB4)	4	
0 dBm (SCB5)	0 dBm (SCB5)	12dBm (SCB3)	5	
-7dBm (SCB6)	-10dBm (SCB6)	11dBm (SCB6)	6	

Calculate number of UEs for each SCB
SCB1 = 1 UE active mode ON
SCB2 = NO UE
SCB3 = 2 UE active mode ON
SCB4 = NO UE
SCB5 = NO UE
SCB6 = NO UE

If SCB have no user assign them to inactive mode i.e. Standby, Sleep or Off based on their rank

Ranking Method of Inactive SCBs

	UE1	UE2	UE3	Average RSS	Mode
SCB2 - RSS	10dBm	40dBm	35dBm	28dBm	Standby
SCB4 - RSS	20dBm	40dBm	12dBm	24dBm	Sleep
SCB5 - RSS	0dBm	0dBm	33dBm	11dBm	Off
SCB6	-7dBm	-10dBm	11dBm	-2dBm	Off

Table 3.1: Mechanism of classification with 6 SCBs and 3 UEs values.

Thus, in this scenario, four different operation modes are considered for the SCBs, and their power consumption is assumed to be as in Table 3.2 (Liu et al., 2015).

Table 3.2: The Power Consumption for Different Sleep Mode

Sleep Mode	Wake-up Time (s)	Power Consumption
On	0	100%
Stand-by	0.5	50%
Sleep	10	15%
Off	30	0

That is SCBs in on, standby, sleep, and off operation modes consume power at rates of 100%, 50%, 15%, and nearly zero, respectively; their related bias function values are ξ^{s}_{on}, ξ^{s}_{sby}, ξ^{s}_{slp}, ξ^{s}_{of}, respectively. Since the MCB serves and controls all SCBs, it is assumed to be active and always in (On) mode consuming 100% of power, and assigned to the bias function as ξ^{m}_{on}. MCBs or any other SCBs are represented as being "active" when they are engaged in the operation mode of (On), while MCBs or other SCBs in standby, sleep, or off are considered to have an "inactive status" (active/inactive status). The repulsive scheme also used in which SCBs can only be placed in inactive modes if they are within the inactive radius, r_{in}, within which they have been placed in inactive mode.

A radius of this size, which is referred to as D, falls under the coverage area of MCB. Using the metric average inactive ratio concept $\bar{\Psi}$ as described by (Zhang et al., 2016), the following calculation is then performed:

$$\bar{\Psi} = \frac{\pi r_{in}^2}{\pi D^2} \tag{3.14}$$

Problem Statement and Solution

This section describes the formulation of the problem and the constraints for the proposed GOA-VPMS algorithm, as well as how the GOA and VPMS algorithm are used to address the problem. Our first step is to formulate the problem as follows:

$$\max_{\xi_{on}^m, \xi_{on}^s, \xi_{sby}^s, \xi_{slp}^s} = \eta EE \tag{3.15}$$

Subject to

$$0 \leq \xi_{on}^m + \xi_{on}^s \leq 0.9 \tag{3.16}$$

$$0 \leq \xi_{sby}^m + \xi_{slp}^s \leq 0.1 \tag{3.17}$$

$$\xi_{on}^m + \xi_{on}^s + \xi_{sby}^s + \xi_{slp}^s \leq 1 \tag{3.18}$$

$$\sum_{s \in S} \Phi_{su} \leq 1; \forall\, u \in U \tag{3.19}$$

$$\Phi_{su} \in \{0, 1\}; \forall s \in S;\ \forall u \in U \tag{3.20}$$

$$count\left(\sum_{u\in U}\Phi_{su}\neq 1\right)\leq \bar{\Psi};\forall s\notin S \qquad (3.21)$$

where constraint (27) indicates that for both operation modes of an active MCB and an active set of SCBs, the bias function value cannot be greater than 90% of the overall bias function value; this is to guarantee the stability of the two-tier network by not greatly reducing the power consumption of the MCB and the active SCBs. According to constraint (28), the bias function of inactive SCBs must not account for more than 10% of the total bias function value; this reflects our main goal, to reduce the power consumption of inactive SCBs as much as possible. Constraint (29) stipulates that the sum of the bias function values for the MCB and both active and inactive SCBs must be less than or equal to 1. Constraint (30) guarantees that only one UE can be connected to a single SCB at a time. Constraint (31), Φ_{su} is a binary digit variable $(0\ or\ 1)$ that represents the user association indication; in other words "1" indicates that the particular UE is connected to one of the SCBs, whereas "0" means the UE is not connected to any SCB. Finally, constraint (32) guarantees that the number of SCBs that can be in inactive operation mode does not exceed the average inactive ratio, $\bar{\Psi}$, to prevent the occurrence of coverage holes.

The Algorithm VPMS

The objective of this algorithm is to calculate the EE of a two-tier network with the cooperation of GOA, which referred to as "Algorithm 1," which generates the bias function values that are fed into the proposed VPMS algorithm, referred to as "Algorithm 2," at the beginning of the simulation. VPMS is responsible for all the various duties that are performed here by the algorithm, such as calculating all possible received signal strength RSS for each UE, sorting the RSS values in ascending order, calculating each mode's power consumption, calculating the total data rate, then obtaining SE and EE. As an example of how a SCB can be classified, each SCB should be assigned a specific mode of operation based on its classification.

The Proposed Algorithm GOA-VPMS

The objective of this algorithm is to maximize the EE of a two-tier network by finding the optimum bias function values. Using the ranking approach, the GOA-based VPMS adaptively selects the appropriate operation mode for each SCB. Pseudo codes are provided to explain the stages of how the two algorithms, GOA and VPMS, jointly cooperate to maximize efficiency in our scenario, as well as additional details on how the GOA-VPMS algorithm can be used to implement the solution. Further details are provided on how the bias function values ($\xi_{on}^{m}, \xi_{on}^{s}, \xi_{sby}^{s}, \xi_{slp}^{s}$) for each BS are used to adjust its network power consumption. Initially, the GOA algorithm generates a random population of various sets of solutions, each of which consists of a set of bias function values (Algorithm 1 summarizes the steps in GOA algorithm). Next, in order to compute the solution's fitness and obtain the EE value, the VPMS algorithm (Algorithm 2) is called, which is subsequently passed back to the GOA algorithm again. Figure 3.2 demonstrates the proposed logic flow diagram.

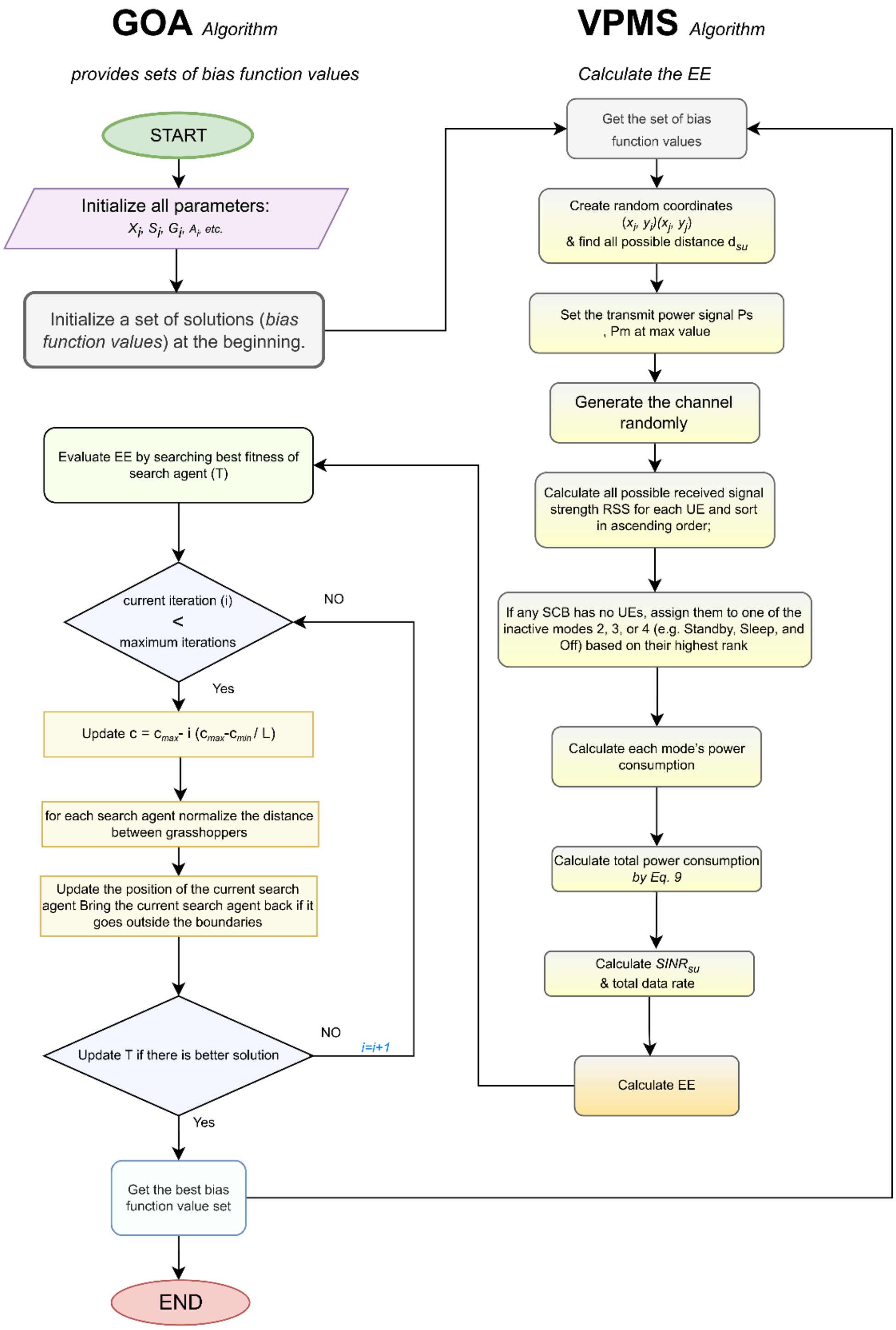

Figure 3.2: The GOA-VPMS logic flowchart

Algorithm 3.1: Grasshopper Optimization Algorithm.

START
Initialize swarm $X_i(i = 1, 2, ..., n)$
Initialize, C_{max}, C_{min}, and maximum number of iterations
Calculate the fitness e.i Algorithm 2;
The best search agent is T
while $i < Max\ number\ of\ iterations$ **do**
  Update, c, using Equation (2.11)
  for $each\ search\ agent$ **do**
    In (Coello, C.A.C 2002; Mirjalili et. al 2014) normalize the distance between grasshoppers.
    Apply Equation (2.10) to update the current position of the search agent
    Restore the current search agent if it crosses the boundaries
  end for
  If there is a better solution, update T
  $i = i + 1$
  Evaluate each search agent's fitness e.i Algorithm 2;
end while
Return T

Algorithm 3.2: Variant Power Mode Selection

START

1. Obtain $\xi_{on}^{m}, \xi_{on}^{s}, \xi_{sby}^{s}, \xi_{slp}^{s}$ from Algorithm 1;
2. Create random coordinates $(x_i, y_i)(x_j, y_j)$;
3. Find all the possible distances d_{su} using Euclidean distance;
4. Set the transmission power signal p_m, p_s at max value for MCB and each SCB;
5. Generate the channel randomly, $h_{su}{d_{su}}^{-\alpha}$, for all possible connections between the UEs and SCBs
6. Calculate all possible received signal strength RSS for each UE;
7. Sort the RSS values in ascending order;
8. Link the users, u, to the SCB, s, that has the highest, RSS;
9. Count the number of users for each SCB;
10. If any SCB has no UEs, assign them to one of the inactive modes 2, 3, or 4 (e.g., Standby, Sleep, and Off) based on their highest rank;
11. Calculate each mode's power consumption;
12. Calculate total power consumption $P_{m,s}^{t}$. Equation (3.9);
13. Calculate each $SINR_{su}$ using Equation (3.2) then the total data rate R_{total} by Equation (3.4),
14. Calculate spectrum efficiency SE_{HetNet} and energy efficiency ηEE by Equations (3.11) and (3.12) respectively;

END

Performance Evaluation Methods

The simulation and analysis of the proposed VPMS based on the GOA algorithm have been carried out as part of this study using the MATLAB program version 2023a on Windows 11 in order to evaluate the performance of the system. The simulation was carried out in the following manner: within the given area, the entire network consists of 50 SCBs S and the number of UEs is assumed to be 200, and the SCBs and UEs are each randomly distributed in accordance with the Poisson point process (PPP). Since LTE-Advance can utilize this bandwidth through channel aggregation and as 100 MHz SCBs are expected to provide ultra-high-speed communications in 5G networks, a 100 MHz network bandwidth was chosen. Both low and high SINR locations can be analysed using the methods described here. Further, the instantaneous SINR values for users indicated by Equation (3.2) may vary depending on the dynamic channel conditions and the location of the UE.

Our primary objective is to optimize all BSs' power consumption to maximize EE across the entire two-tier network. At the beginning, all MCBs and SCBs in the network have their transmission power set to maximum. After running the GOA and VPMS algorithms, the optimum bias function values obtained from the simulation, such as $\xi_{on}^{m^*}$, $\xi_{on}^{s^*}$, $\xi_{sby}^{s^*}$, and $\xi_{slp}^{s^*}$, which refer to MCB (on) and SCB (on, standby and sleep) operation modes, respectively. Table 5 demonstrates our findings for various values used to evaluate the performance of the VPMS-GOA algorithms.

The following metrics are derived for the two-tier communication network architecture based on the proposed two-tier architecture:

- Signal-to-Interference-plus-Noise Ratio ($SINR$).
- Received Signal Strength (RSS).
- Index of user association (Φ_{su})
- power consumption of each BS (P_m, P_s).

Thus, in order to analyse spectrum efficiency and energy efficiency, calculations are made to be able to determine their efficiency.

A comparison was made between the Switching Off Decision and User Association (SODUA) and Power Mode Variant Selection (PMVS) algorithms, on the basis of energy efficiency (EE) and spectral efficiency (SE), to evaluate the performance of the GOA-VPMS algorithm. The bias function value also adjusted for one of the bias functions and relaxed the others so that we can compare and evaluate the performance of our proposed scheme in more detail. The convergence of the Grasshopper Algorithm (GOA) and the Genetic Algorithm (GA) is further described and compared through more comparisons and discussions in the following chapter.

CHAPTER IV

Findings and Discussion

Throughout this chapter, the simulation environment demonstrated and present the results related to the research hypotheses. Additionally, the convergence curves for GOA and GA as well as their performance explored.

Simulation Results and Discussion

To demonstrate the proposed approach for determining SCB operating patterns, the simulation results presented.

After running the GOA and VPMS algorithms, the optimum bias function values obtained from the simulation, such as $\xi_{on}^{m^*}$, $\xi_{on}^{s^*}$, $\xi_{sby}^{s^*}$, and $\xi_{slp}^{s^*}$, refer to MCB (on) and SCB (on, standby and sleep) operation modes, respectively. Table 4.2 shows our results with different values.

Table 4.1: Simulation results and values

Operation Mode	MCB/SCBs Sets	Optimal Bias Function	Value
ON	MCB	$\xi_{on}^{m^*}$	0.490
ON	S_{on}	$\xi_{on}^{s^*}$	0.401
STANDBY	S_{sby}	$\xi_{sby}^{s^*}$,	0.061
SLEEP	S_{slp}	$\xi_{slp}^{s^*}$	0.035
OFF	S_{of}	$\xi_{of}^{s^*}$	-

Findings and Discussion for Research Hypothesis I

From Table 4.2, the findings show that the bias function values $\xi_{on}^{m^*}$ and $\xi_{on}^{s^*}$ have only been reduced to 0.490 and 0.401, respectively, which are much higher than the bias function values of SCBs that are in active operation mode (e.g., $\xi_{sby}^{s^*}$, and $\xi_{slp}^{s^*}$). This returns to the fact that the MCB is in active operation mode, which refers to controlling all the duties of the network, and a set of SCBs are in active operation mode too, which refers to serving UEs. Therefore, when a set of SCBs is active and in (on) operation mode, they will consume more power than sets of SCBs that are in inactive operation modes, such as standby, sleep, or off, to serve users, because they are active. However, there should be a limit on the bias function values of both MCBs and SCBs that are in (on) operation mode, so as to ensure that they do not exceed 90% of the total bias function value as constrained by (27). As can also be seen from Table 5, the lowest values of the optimum bias function obtained by the GOA-VPMS algorithm are associated with the sets of SCBs, $\xi_{sby}^{s^*}$, and $\xi_{slp}^{s^*}$, which are most reduced at 0.061 and 0.035 respectively. In this way, it reflects the objective of the study, which is to reduce the power consumption of these modes of operation as much as possible, as part of its overall aim. The relevant bias function values, however, do not exceed 10% of the overall bias function value since the related bias function values are constrained by the rule of (28). Our scheme (referred to as GOA-VPMS for simplicity) compared with the following schemes: conventional sleep control, without sleep control, random sleep 20%, and random sleep 30%, in order to see how each scheme compares to the other in terms of the difference in power consumption in all schemes as the number of SCBs varies.

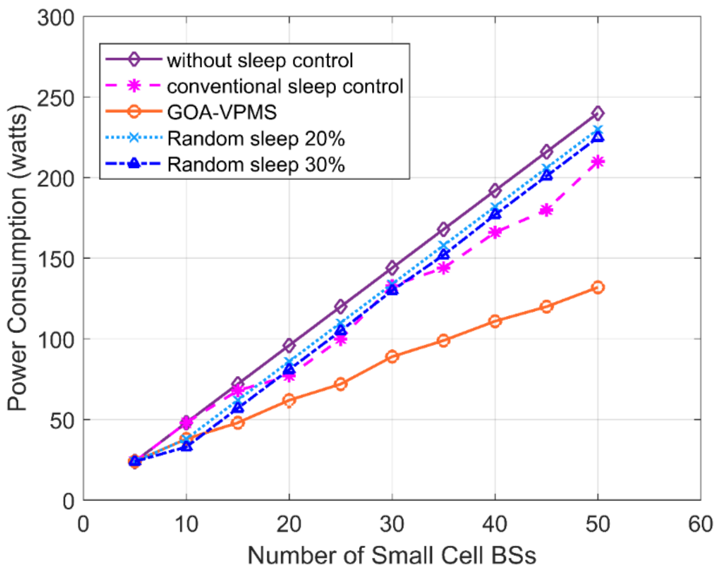

Figure 4.1: Power consumption as the number of SCBs changes

The figure 4.1 shows that there is a proportional relationship between the number of SCBs and their power consumption; in other words, as the number of SCBs increases, the amount of power consumed by all schemes also increases as well. In contrast, the considered system model shows that the conventional sleep control scheme has a relatively lower power consumption when compared to the consideration system model. On the other hand, the scheme of random sleep 20% consumes slightly more power than the scheme of random sleep 30% and the conventional sleep method, which consumes slightly less power. The simulations, however, show that all previous schemes, such as those without sleep control, conventional sleep control, random sleep 20%, and random sleep 30%, are all outperformed by the proposed GOA-VPMS by 66.04%, 54.72%, 49.06%, and 44.65%, respectively, when compared with the previous schemes. The reason for this is that in our design scheme, load or traffic variations are not taken into account.

Findings and Discussion for Research Hypothesis II

Further to evaluating the performance of the GOA-VPMS algorithm, we compare it with both the Switching Off Decision and User Association (SODUA) and Power Mode Variant Selection (PMVS) algorithms from an EE point of view, as shown in Figure 4.2.

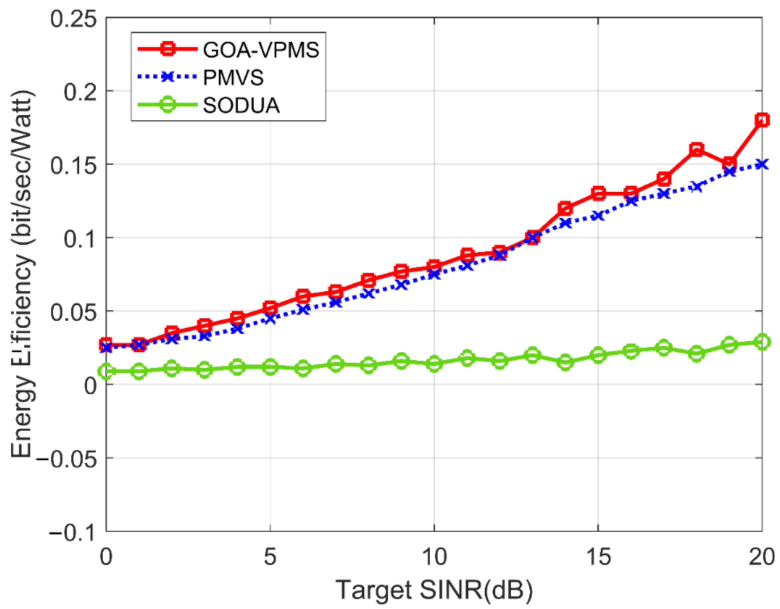

Figure 4.2: EE for GOA-VPMS vs. SODUA and PMVS algorithms.

The proposed algorithm outperforms both the SODUA and PMVS algorithms in terms of maximizing EE by 67.23% and 9.38%, respectively, in line with expectations as it outperforms them both in terms of efficiency.

Findings and Discussion for Research Hypothesis III

The GOA-VPMS algorithm is compared to both the Switching Off Decision and User Association (SODUA) and Power Mode Variant Selection (PMVS) algorithms from a spectrum efficiency perspective. It can be seen from Figure 4.3 that the performance of the GOA-VPMS algorithm can be compared with that of both the Switching Off Decision and User Association (SODUA) and Power Mode Variant Selection (PMVS) algorithms, from the point of view of spectrum efficiency.

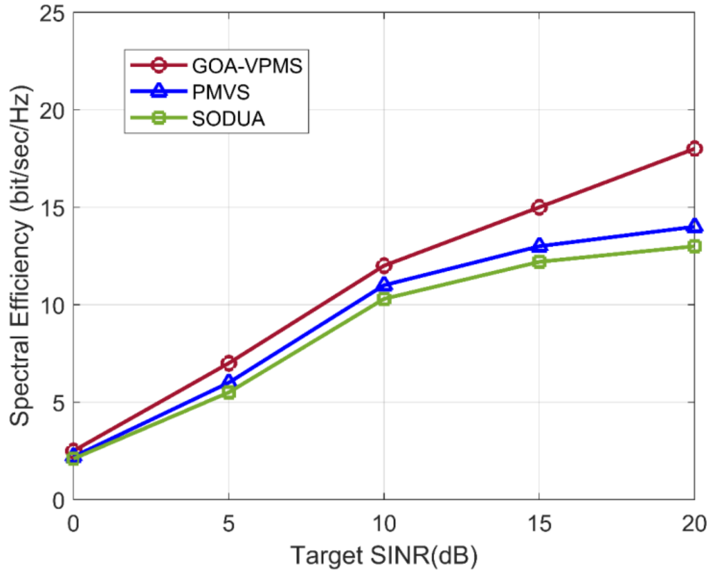

Figure 4.3: Spectrum efficiency for GOA-VPMS vs. SODA and PMVS algorithms.

As expected, the proposed algorithm outperforms both the SODUA and PMVS algorithms in terms of enhancing SE by 20.9% and 15.23%, respectively, for the entire two-tier network, which is consistent with expectations. The reason for this is that the SODUA algorithm only considers the switched-off mode of the SCB, whereas our GOA-VPMS algorithm considers four different operating modes of the device (e.g., on, standby, sleep, and off). A further advantage of GOA is that it is able to outperform other algorithms in the literature, as mentioned in (Saremi et al., 2017), e.g., GA (Genetic Algorithm), resulting in superior performance.

Findings and Discussion for Research Hypothesis IV

Furthermore, the value of one bias function fixed and relaxed the other bias function values for better comparison and evaluation of the performance of our proposed scheme. The findings demonstrate that the EE is still optimized despite the bias function values varying from 0 to 0.9 and from 0 to 0.1, respectively, even though the bias function values vary. Clearly, in Figure 4.4, it can see that maximizing the efficient energy of the scheme is a trade-off between the values of the bias function and maximizing EE, where the curve related to the MCB in (on) operation mode is slightly decreased, which indicates a minimal reduction in power consumption, but that the curve related to the SCB (on) operation mode gradually decreases, indicating a reduction in power consumption and therefore a greater reduction in energy efficiency.

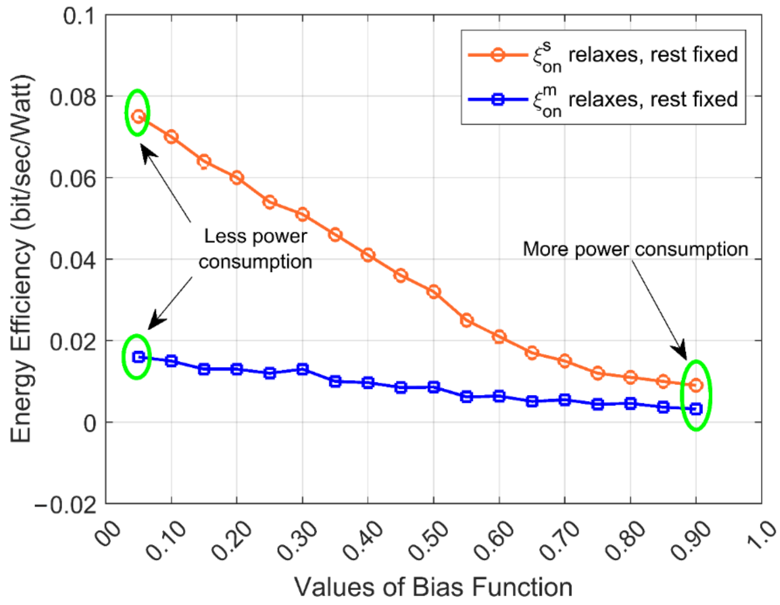

Figure 4.4: Bias function values of MCB and SCBs.

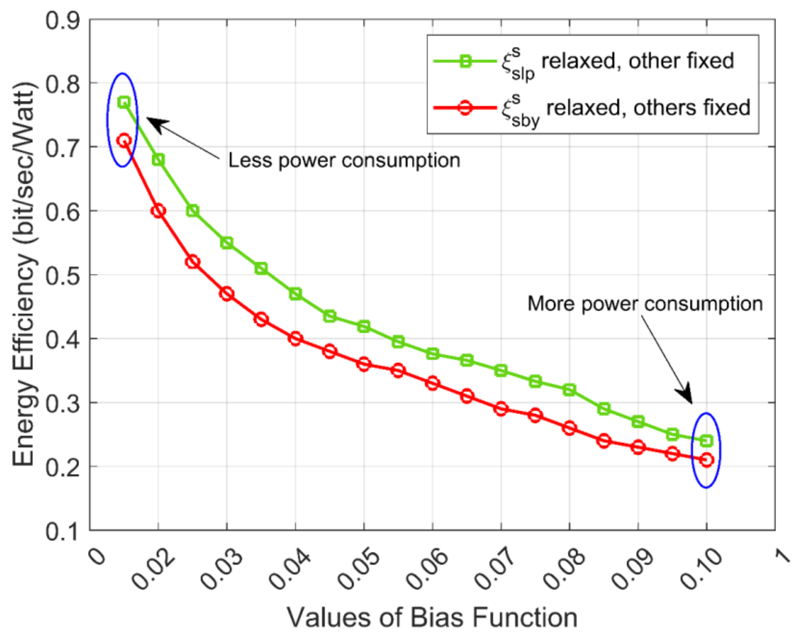

Figure 4.5: Bias function values of SCBs for Standby, and Sleep operation mode.

Nevertheless, Figure 4.5 shows that the most significant reduction in power consumption for inactive SCBs in (standby) and (sleep) modes of operation is the reduction in power consumption for inactive SCBs in both modes.

GOA and GA Convergence Curves Discussion

An illustration of the convergence curves of GOA and GA at multiple time intervals can be seen in Figure 4.6 - 4.11. A solution can be obtained for each algorithm through the number of iterations which are required to obtain a solution. By studying the curves, it is also possible to determine which algorithm offers the best solution for each problem. Figures 4.6 and 4.7 show that in the first case, the GOA algorithm is able to reach the most optimal solution before the GA algorithm is able to reach it. Furthermore, Figure 4.8 and 4.9 show that in the second-time run of the GA model, GOA performs better than GA in terms of requiring fewer iterations to reach the optimum value of the bias function than GA. However, in Figure 4.10 and Figure 4.11 there appears to be a minimal difference between both GOA and GA, when it comes to reaching the best solution.

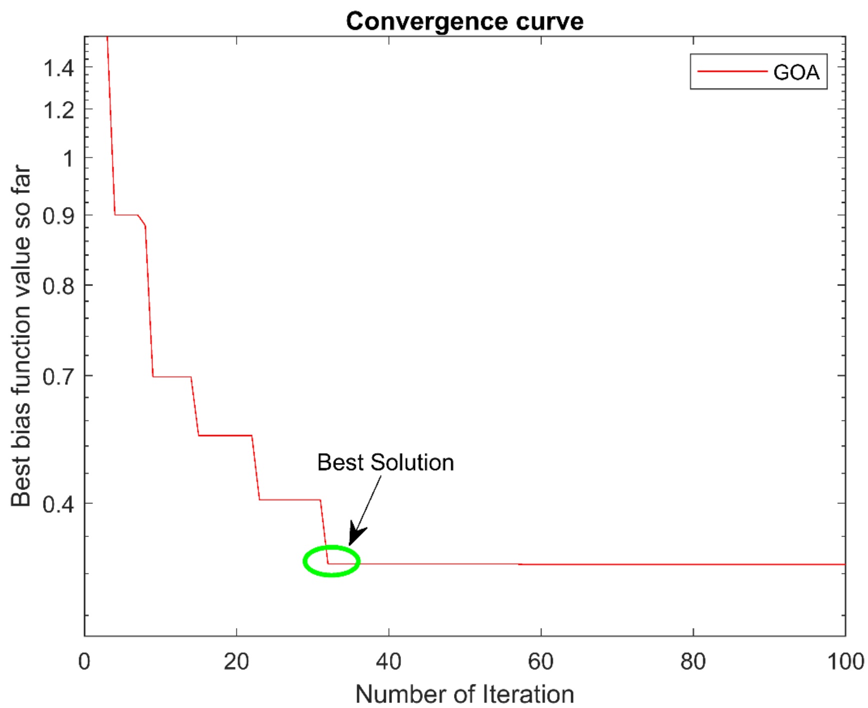

Figure 4.6: The convergence curve for GOA first-time run.

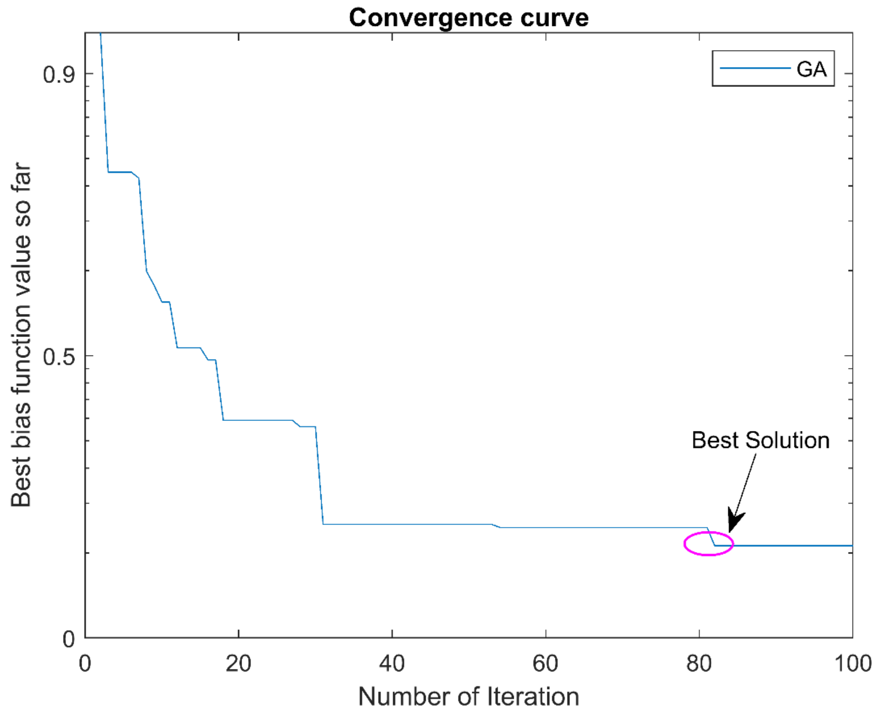

Figure 4.7: The convergence curve for GA first-time run.

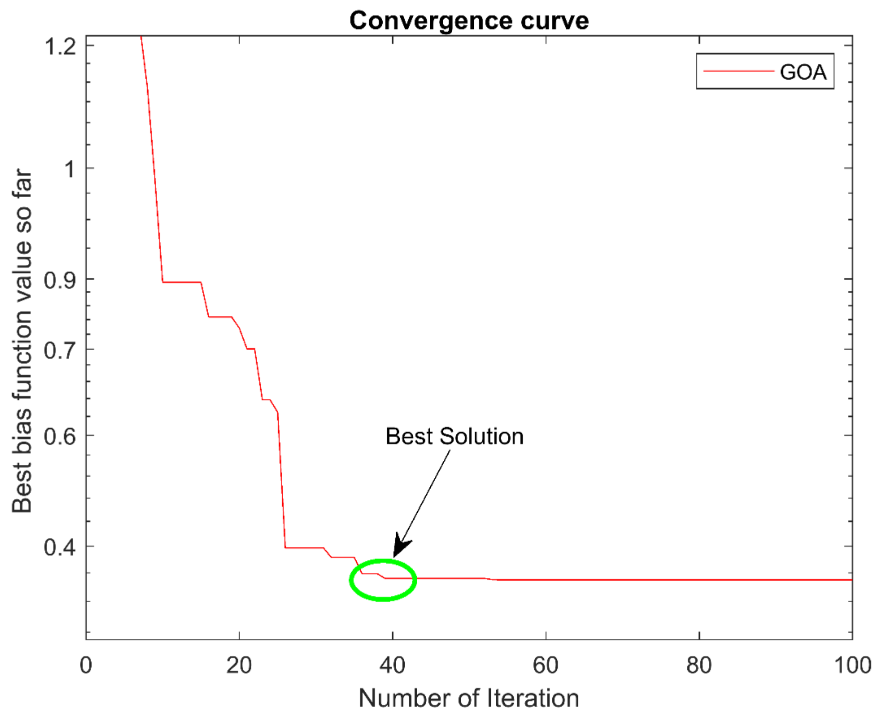

Figure 4.8: The convergence curve for GOA second-time run.

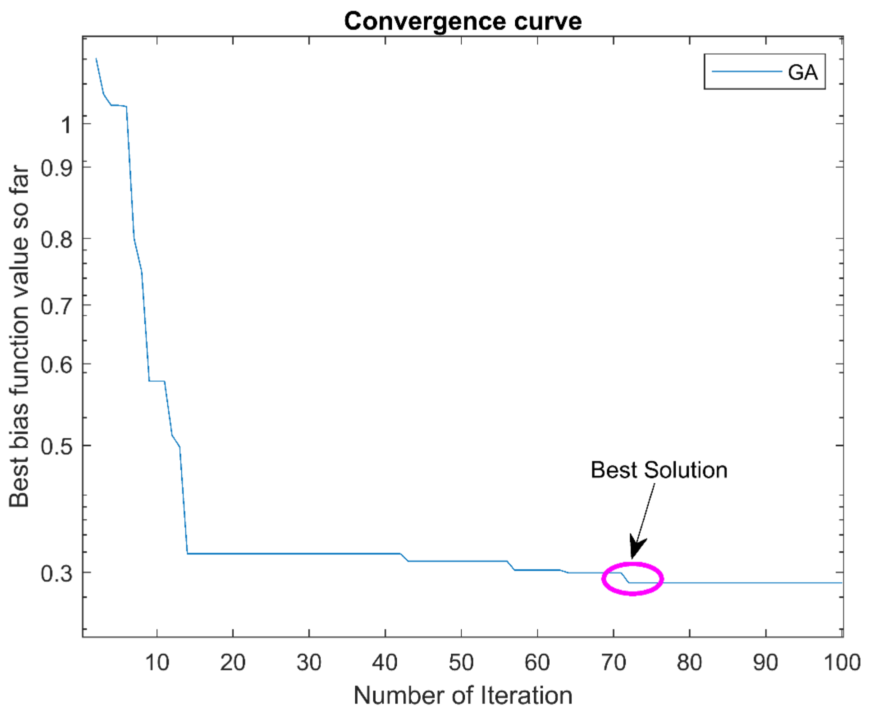

Figure 4.9: The convergence curve for GA second-time run.

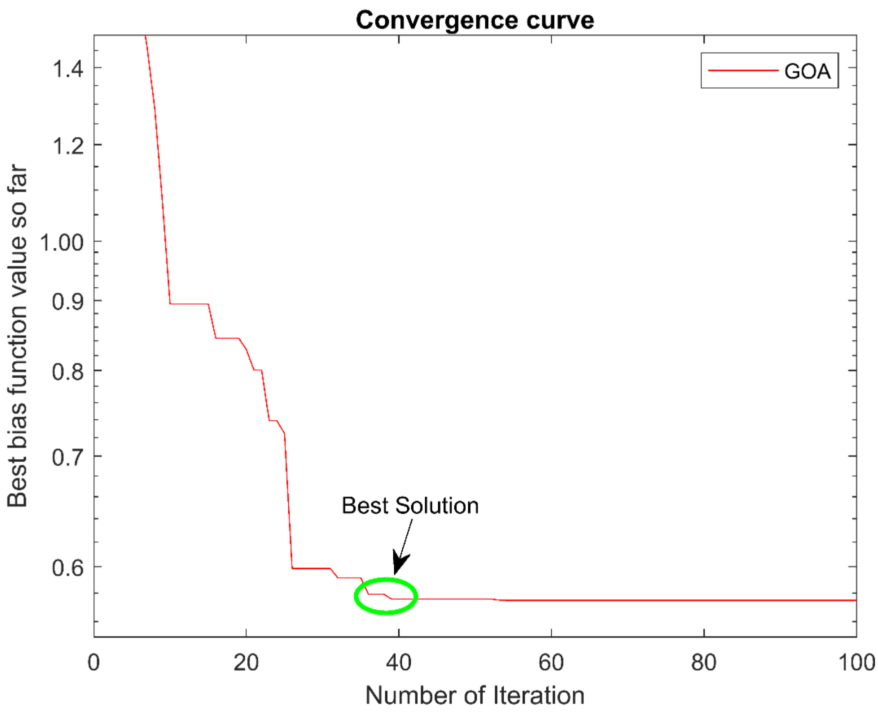

Figure 4.10: The convergence curve for GOA third-time run.

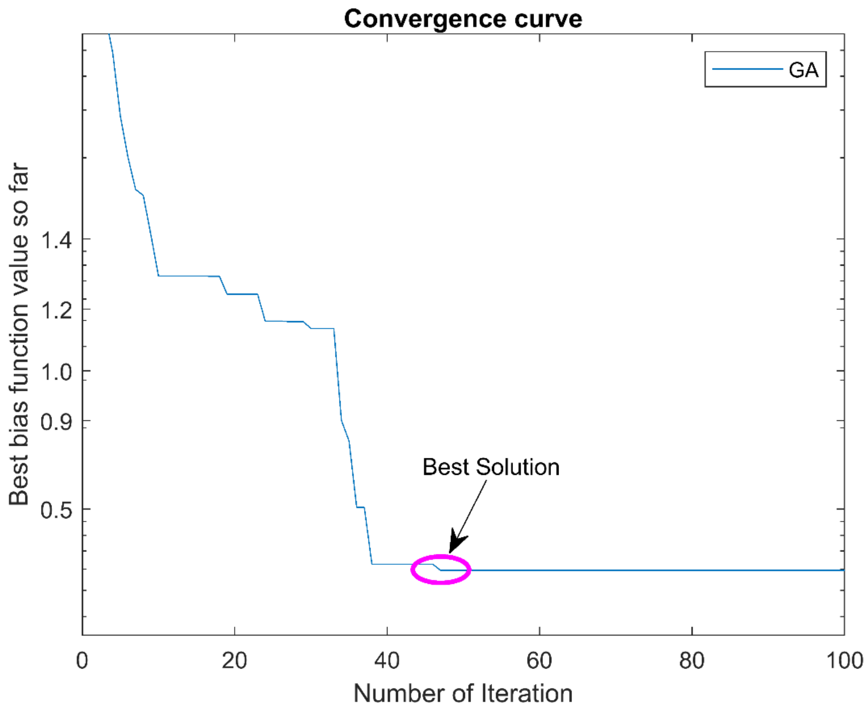

Figure 4.11: The convergence curve for GA third-time run.

Based on the results of this study, it concluded that both GOA and GA can solve this problem efficiently. Our goals can be achieved through either of these methods because they work very similarly. However, (Cikan et al., 2022) stated that no single optimization can solve all problems. In other words, any other optimization is not guaranteed to produce the same results.

CHAPTER VI

Conclusion and Recommendations

Conclusions

The energy consumption of mobile communication networks has recently received much attention as one of the critical issues related to global warming. Energy consumption in the ICT industry constitutes a significant proportion of overall energy consumption in the industry. A bio-inspired behaviour-based mechanism is described in our study as a way of selecting a suitable SCB operation mode among on, standby, sleep, and off modes. In order to manage the power consumption of each operation mode, by utilize a bias function. In each SCB, there are four different power modes that can be selected. Calculations were made for the two-tier networks' signal-to-interference noise ratio (SINR), user-SCB association index, power consumption, and maximizing the EE for the proposed system by applying the VPMS-GOA algorithm. In terms of power consumption, the proposed algorithm scheme outperforms state-of-the-art algorithms, including those without sleep control, conventional sleep control, random sleep 20%, and random sleep 30%, by 66.04%, 54.72%, 49.06%, and 44.65%, respectively. The reason for this is that our algorithm does not take into account traffic or load variations. In addition, the proposed algorithm outperforms the SODUA and PMVS algorithms in terms of maximizing EE and enhancing SE by 67.23% and 9.38%, respectively.

Recommindations

In reality, there are more MCBs and several SCBs than in this small scenario, so the power consumption and EE are not likely to be as significant in this example compared to a scenario with more MCBs and several SCBs. More research into the energy consumption of UEs in a multi-macrocell environment can be done in the future, since communicating with an MCB requires more energy and the distance between a UE and an MCB is often much greater than the distance between a UE and a local SCB.

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Appendices

Curriculum Vitae

Personal information:

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Nationality: Libyan's

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Objective:

- Continually learning and developing personal potential in diverse environments; motivation and determination to work in different environments.

Educational Qualifications

- PhD Student (2017-2023) (Near East University, TRNC)
- Master of Science in Tele-Communication Engineering (2003-2005) (Brno University, Czech Republic)
- Advanced Higher Diploma in Aircraft Maintenance Engineering (1992-1995) (Higher Institute of Civil Aviation and Metrology, Esbiaa, Libya).
- High School Certificate (1989-1992) (Sidi El-Sayeh High School, Gasr Bin Gashir, Libya).

Employment History

- Head of the Department and Assistant lecturer in information technology (IT) – Higher Institute of Occupational Health and Safety – Tripoli Libya (2008 – 2014).
- Instructor in computer science– Higher Institute of Occupational Health and Safety – Tripoli, Libya (2005 – 2008).
- Technician in the Physics Lab - Higher Institute of Occupational Health and Safety – Tripoli, Libya (1998 – 2002).

Courses/Seminars Attended

- Computers troubleshooting and maintenance
- Wireless network management
- Web design and content management
- Optical Fibre testing and maintenance
- Safety Management course
- Personal Protective Equipment

Languages

- Arabic Native Language
- English very good (spoken & written) (IELTS score of 6.0 at Leeds English Language School in Leeds, UK)
- Czech good

Publications

Sherif, Ashraf, and Huseyin Haci. 2023. "A Novel Bio-Inspired Energy Optimization for Two-Tier Wireless Communication Networks: A Grasshopper Optimization Algorithm (GOA)-Based Approach" *Electronics* 12, no. 5: 1216. https://doi.org/10.3390/electronics12051216

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