Performance Analysis of Biological Resource Allocation Algorithms for Next Generation Networks

Msc Thesis

Thabelang Sefako

A thesis submitted in fulfilment of the requirement for the degree of

MASTER OF SCIENCE IN ENGINEERING (ELECTRONIC)

School of Engineering
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September, 2020

As the candidate's supervisor, I have approved this thesis for submission.

Signed. .Date......08/09/2020.......................

Name: Prof. Tom Walingo

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The following journal/conference papers have emerged from this work and have been accepted for publication or are under review:

1. **Thabelang Sefako and Tom Walingo**, "Alternative Energy Efficient Resource Allocation Algorithms for Uplink LTE-A Networks", in Transactions on Emerging Telecommunication Technologies (Under review)

2. **Thabelang Sefako and Tom Walingo**, "Application of Biological Resource Allocation Techniques to SCMA NOMA Networks", in Proceedings of IEEE AFRICON 2019, Accra, Ghana.

3. **Thabelang Sefako and Tom Walingo**, "Biological Resource Allocation Algorithms for Heterogeneous Uplink PD-SCMA NOMA Networks", in press of IEEE ACCESS

Dedication

I would like to express great gratitude to the sovereign Lord. I would like to dedicate this work to my family, my aunt Mamoqhoai Lydia Ntokoane, and my late mother Marelebohile Matilda Sefako.

Acknowledgements

I am thankful to the almighty God for blessing me with the strength and patience to compile this work. I am greatly indebted to my supervisor Prof. Tom Walingo, for his advice and expertise in guiding me throughout the project. Without his constructive comments and corrections, and positive motivation, I would not have been able to complete this study. I would also like to thank the University of Kwazulu-Natal in particular the CRART centre for the financial help it provided towards subsistence costs and other related costs in support of the research study.

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Abstract

In recent years there has been a growing need for ubiquitous access to wireless network services. Wireless networks are expected to deliver specific minimum quality of service (QoS) requirements regarding high data rates, lower latency, and low power consumption to user mobile devices. Satisfying these increasing QoS expectations in recent wireless networks such as fourth generation (4G) and fifth generation (5G) is affected by challenges including spectrum efficiency, energy efficiency and interference among others. To address these challenges there is need to develop better media access control (MAC) protocols, implement changes in architectural infrastructure incorporating macro and small cells to enable higher capacity, and design appropriate resource allocation (RA) optimization algorithms based on modern artificial intelligence (AI) algorithms such as biologically inspired algorithms. With this perspective, his work considers the application biologically inspired algorithms for uplink RA in 4G and 5G scenarios.

In the first part of the work, Long Term Evolution Advanced (LTE-A) which is a ratified access technology for 4G is considered. A heterogeneous network (HetNet) model based on macro and small cells is developed. In particular, the focus is on the uplink which employs Single Carrier Frequency Division Multiple Access (SC-FDMA). SC-FDMA technology requires special resource block allocation patterns due to the subcarrier adjacency and exclusivity restriction resulting in resource allocation problems. Unlike traditional analytical combinatorial resource allocation schemes, this work proposes alternative biological inspired resource allocation schemes for SC-FDMA due to their advantages of simple implementation compared to other analytical methods. The performance of the developed schemes, Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO) and the proposed hybrid Adaptive Particle Ant Swarm Optimization (APASO), is investigated and compared to that of the analytical model based on Lagrangian optimization. The performance and complexity of the biological algorithms is observed to be near-optimal with APASO outperforming the traditional PSO and ACO algorithms in resource allocation.

The second part of the work considers RA in 5G NOMA access schemes that are able to multiplex multiple users on a resource element. The features of 5G heterogeneous networks have necessitated the development of hybrid NOMA schemes combining the merits of the individual NOMA schemes for optimal performance. Considering a HetNet scenario, a hybrid access model based on power domain NOMA (PD-NOMA) and sparse code multiple access (SCMA) referred to as power domain sparse code multiple access (PD-SCMA) is developed. The hybrid technologies on 5G networks make complex air interfaces resulting in new resource allocation (RA) and user pairing (UP) challenges aimed at limiting the multiplexed users interference. Furthermore, common analytical techniques for evaluating the performance of the schemes lead to unrealistic network performance bounds necessitating alternative schemes. This work explores the feasibility of a hybrid power domain sparse code non-orthogonal multiple access (PD-SCMA) that integrates both power and code domain multiple access on an uplink network with small cell user equipments (SUEs) and macro cell user equipments (MUEs). Alternative biological RA/UP schemes; the ant colony optimization (ACO), particle swarm optimization (PSO) and a hybrid adaptive particle swarm optimization (APASO) algorithms, are proposed. Performance results indicate that the developed APASO outperforms both the PSO and ACO in sum rate and energy efficiency optimization on application to the PD-SCMA based heterogeneous network. In general, APASO appears to outperform PSO and ACO by more than 14.39% while its best saturation performance is approximately 8.22% of Langragian technique.

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List of Acronyms

1G	First Generation
2G	Second Generation
3G	Third Generation
4G	Fourth Generation
5G	Fifth Generation
3GGP	3rd Generation Partnership Project
ACO	Ant Colony Optimization
APASO	Adaptive Particle Ant Swarm Optimization
AMPS	Advanced Mobile Phone System
AWGN	Average White Gaussian Noise
BER	Bit Error Rate
BIP	Binary Integer Problem
CSI	Channel State Information
CDMA	Code Division Multiple Access
EE	Energy Efficiency
eNodeB	E-UTRAN NodeB
EPS	Evolved Packet System
FBS	Femtocell Base Station
FDMA	Frequency Division Multiple Access

FUE	Femto User Equipment
Gbps	Giga bits per second
GSM	Global System for Mobile Communication
HetNets	Heterogeneous Networks
IoT	Internet of Things
LTE-A	Long Term Evolution Advanced
Mbps	Mega bits per second
MBS	Macrocell Base Station
MPA	Message Passing Algorithm
MIP	Mixed Integer Problem
MUE	Macro User Equipment
NGWNs	Next Generation Wireless Networks
NOMA	Non-Orthogonal Multiple Access
OFDMA	Orthogonal Frequency Multiple Access
OMA	Orthogonal Multiple Access
PDN	Packet Data Network
PSO	Particle Swarm Optimization
PD-NOMA	Power Domain Non-Orthogonal Multiple Access
QoS	Quality of Service
QoE	Quality of Experience
RF	Radio Frequency
SC-FDMA	Single Carrier Frequency Division Multiple Access
SCMA	Sparse Code Multiple Access
SIC	Successive Interference Cancellation
SINR	Signal to Interference Noise Ratio
UE	User Equipment

UMTS	Universal Mobile Telecommunication System

Preface

“When wireless is perfectly applied the whole earth will be converted into a huge brain, which in fact it is, all things being particles of a real and rhythmic whole. We shall be able to communicate with one another instantly, irrespective of distance."

—Nikola Tesla

University of KwaZulu-Natal, September 8, 2020

Part I

Introduction

1 Introduction and Background

In modern society, wireless communication plays an important part in different aspects of life. There exist numerous instances of how wireless communication has revolutionized living standards of modern society. The proliferation of smart phones provides a platform for a wide variety of end-user mobile applications which have increased meteorically in recent years. A vast range of services can now be offered using mobile communication devices. For instance, smart phones can be equiped with life-saving technology (e.g. tele-medicine apps) which provides access to medical services to improve lives of people in remote areas. They can also provide education based services such as tele-education, or marketing services for business environments like tele-marketing. Mobile users also rely heavily on their mobile phones as they navigate many other different aspects of their lives. The applications that they use require specific quality of service (QoS) requirements from operators such as higher data rate and reduced power consumption for their mobile terminals. Needless to say, mobile communication is no longer a luxury but it is now a necessity to have in order to sustain a reasonable quality of life.

The high demand for ubiquitous access to wireless communication services has increased the need for access to network resources from consumers. To service this increasing user demands enhanced media access control (MAC) protocols need to be implemented together with changes in infrastructure architecture (including macro and small cells) to increase capacity. Improved RA algorithms motivated by latest artificial intelligence (AI) algorithms such as nature-inspired algorithms need to be applied for RA in wireless communication networks. As radio spectrum is a finite and scarce resource [1], hence resource management in next generation wireless networks (NGWNs) is crucial in servicing user demand. In light of this realization, research in resource allocation in NGWNs has intensified in recent years. Motivated by this perspective this work focuses on developing MAC protocols and effecting infrastructure changes using macrocells and small cells to increase capacity, and applying RA algorithms based on biologically inspired algorithms to optimize sum-rate and energy efficiency of uplink long term evolution advanced (LTE-A) and non-orthogonal multiple access (NOMA) 5G networks. We consider resource allocation using metaheuristic algorithms as alternatives to widely investigated analytical techniques.

This chapter outlines evolution of wireless networks, conducts literature review on fourth generation networks including LTE-A MAC protocols, and 4G challenges and mitigation strategies. Literature review on fifth generation networks, macrocell and small cell architectures, and non-orthogonal multiple access (NOMA) schemes is also presented. After discussing 5G challenges and existing mitigation strategies, the research problem is formulated followed by vividly explained research objectives and methodology .

2 Evolution of wireless networks

The evolution of wireless communication networks from the 1st generation which provided voice-based 2G GSM networks to all IP-based 3G, 4G and 5G networks has been fueled by the ever-increasing demand for high quality services by consumers [2]. The first generation (1G) of mobile phones invented in the early 1980s provided only voice services based on Advanced Mobile Phone System. It was based on frequency division multiple access (FDMA) using a bandwidth of 824-894 MHz and speed of 2.4 kbps [2]. It relied solely on 150MHz analog signal and suffered from poor voice quality, poor handoff, poor battery life and security [3]. The second generation (2G) of wireless networks employing global system for mobile communication (GSM) surfaced in the late 1980s [4]. These systems utilized digital signals and could provide text and pictorial messages. They operated in a bandwidth of 30 to 200 KHz. Although they offered improved voice quality and multimedia message (MMS) services at low speeds they could not handle video content and still experienced coverage challenges in areas where digital signals were weak.

Third generation (3G) technology which combined Time Division Multiple Access (TDMA) and GSM emerged in the year 2001 [5]. These systems based on packet switching technology consist of a core network and radio access network provides CDMA2000, Wideband-CDMA, and World-wide Interoperability for Microwave Access (WiMax). Third generation networks referred to as universal mobile telecommunication system (UMTS) offered data services with higher speed, more bandwidth and faster data rates enabling internet protocol (IP) based applications with video content [6]. Fourth generation networks which utilized orthogonal frequency division multiple access (OFDMA) in downlink and single-carrier frequency division multiple access (SC-FDMA) in uplink transmission were subsequently developed to improve on 3G [7]. The 3rd Generation Partnership Project (3GPP) defined the standards for Long Term Evolution Advanced (LTE-A) to serve as the 4G standard besides WiMax [8]. Due to higher data rates, services such as multimedia messaging, video chatting, and high definition TV content is provided by the 4G based networks. Fifth generation (5G) networks which are currently under development are aimed at providing ubiquitous and massive connectivity, high data rates, very low end-to-end latency, higher energy efficiency and efficient spectrum utilization [9]. Various multiple access schemes such as Non-orthogonal multiple access (NOMA), massive MIMO, filtered multicarrier waveforms such as generalized frequency division multiplexing (GFDM), filter bank multicarrier (FBMC), universal filtered multicarrier (UFMC), etc are expected to be adopted in implementing 5G technologies [10]. 5G is anticipated to have a vast range of applications from personal usage in virtualized homes with internet of things (IoTs), reliable healthcare systems, to large-scale industrial applications in automation (e.g. self-driving vehicles) and smart grids [11]. An elaborate account summarizing the evolution of wireless networks is presented in [8]. This work focuses on capacity improvement of 4G and 5G networks. Their architectures, protocols and challenges are discussed in the sections that follow.

3 Fourth generation (4G) networks

3.1 LTE/LTE-A Architecture

Long Term Evolution (LTE) supports only packet-switched networks in contrast to prior cellular systems which also employed circuit-switched technology. The architecture comprises of evolved packet system (EPS) which is responsible for routing IP traffic from a packet data network (PDN) to UE [12]. Figure 1 shows components of the EPS that include the mobility management entity (MME), serving gateway (S-GW), eNodeB (eNB) as well as associated interfaces between the nodes. The eNodeBs are interconnected using the X2 interface and connected to the evolved packet core (EPC) by S1 interfaces [12]. Although the 3GPP defines standards regarding how resource allocation can be carried out in 4G networks, operators can implement RA depending on their own requirements [13]. For instance, the eNB in figure 1 can be employed to implement RA algorithms for handling user scheduling functions. The RA on the X2 interface is the subject of this work.

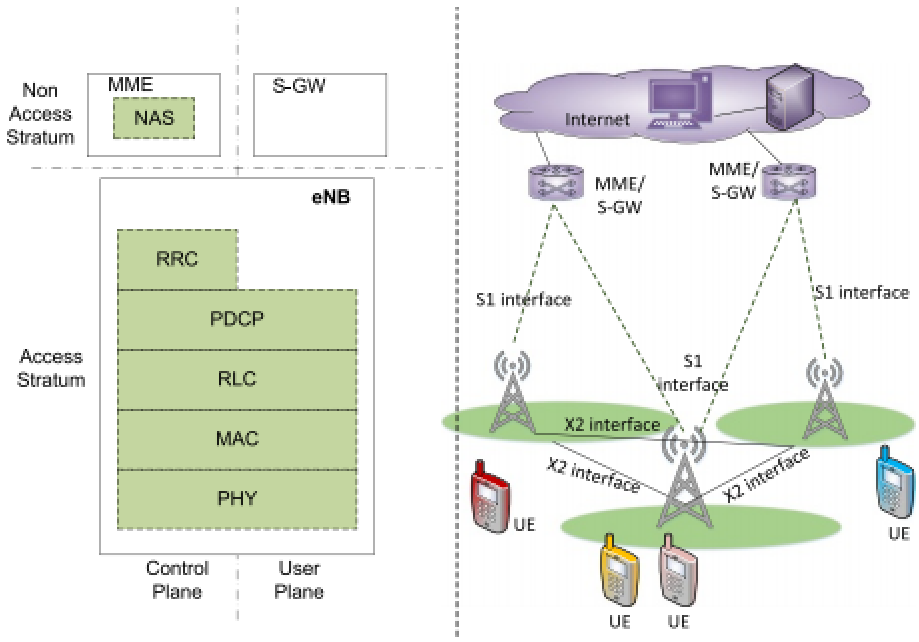

Fig. 1: 4G LTE/LTE-A architecture [14]

3.2 LTE-A Protocols

3.2.1 Orthogonal Frequency Division Multiple Access (OFDMA)

In OFDMA systems, both time and/or frequency resources are used distinguish multiple user signals as shown in figure 2 [15]. LTE-A utilizes OFDMA in downlink to simultaneously assign subcarriers to users. OFDMA is advantageous as it achieves enhanced spectrum utilization and can easily adapt to challenging channel conditions without complex time-domain equalization. It can reduce intersymbol interference (ISI) and is robust against narrow-band co-channel interference [16]. However, OFDMA also suffers from drawbacks such as sensitivity to Doppler shifts, sensitivity to carrier frequency offset and drift than single carrier systems.

The following works consider applications RA in OFDMA. An investigation of multi-user diversity of OFDMA for different scheduling algorithms such as max-rate, proportional fair scheduling, rate craving greedy algorithm, etc. is performed in [17]. The performance of the algorithms is evaluated in terms of fairness and throughput. The performance of OFDMA based RA schemes using uniform and dynamic power allocation in LTE multi-user and multicasting scenarios is considered in [18]. A joint chunk, power and bit allocation is proposed to solve the RA problem. Optimal power allocation techniques in OFDMA femtocell networks are developed in [19]. Lagrangian based convex optimization methods are employed to derive optimized EE solutions.

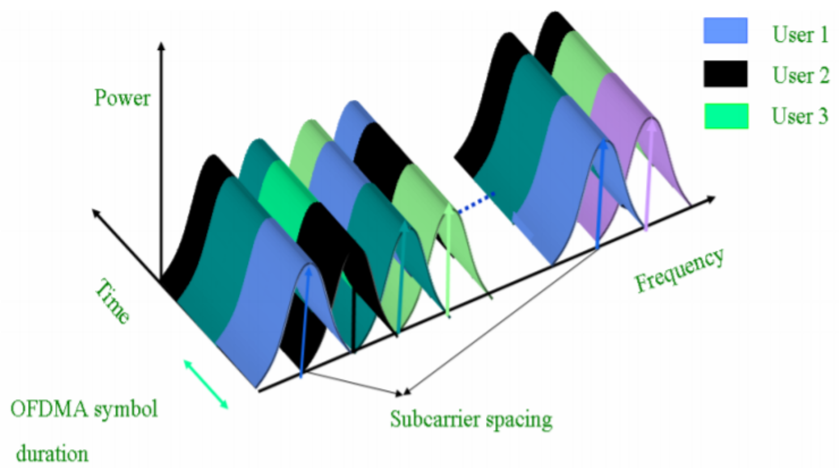

Fig. 2: 4G OFDMA architecture [15]

3.2.2 Single Carrier Frequency Division Multiple Access (SC-FDMA)

SC-FDMA also referred to as Discrete Fourier Transform (DFT) spread OFDM has been adopted by 3GPP as uplink LTE communication method. SC-FDMA utilizes single carrier modulation at the transmitter while frequency domain equalization is applied at the receiver [20]. A major advantage of SC-FDMA over OFDMA in uplink communications is that it has lower peak average power ratio (PAPR) that helps to prolong UE terminal battery life [21] . A drawback of SC-FDMA is its inherent contiguity constraint that requires that if a user is to be assigned two or more resource blocks (RBs), such RBs should be adjacent to each other [22]. This forms part of the investigation of this work. Figure 3 shows the architecture of SC-FDMA transmission and receiving scheme showing processes that input data undergoes in SC-FDMA. At the transmitter a baseband modulator converts binary input to a multilevel sequence of complex numbers followed by a discrete Fourier transform (DFT) process that produces a frequency domain representation of the input symbols. After the subcarrier mapping process, steps similar to OFDMA such as cyclic prefix insertion and parallel to serial conversion are performed before the signal is transmitted through the wireless channel and data recovered in the receiver by reversing processes carried out at the transmitter. A thorough account of the mechanics behind SC-FDMA processes is presented in [23].

The following works consider RA in SC-FDMA. QoS based RA in SC-FDMA is examined in [24]. Matching and resource assignment algorithms are applied to different data traffic types, and their performance analyzed. RA implementing power efficient scheduling in uplink localized SC-FDMA is addressed in [25]. Mathematically based methods incorporating column-generation are applied to derive optimal methods. Adaptive RA to maximize sum-rate given proportional rate constraints in uplink SC-FDMA is addressed in [26]. A Lagrangian based sub-optimal algorithm is proposed. Channel aware LTE-A uplink RA scheduling algorithm is introduced in [27]. The proposed algorithm utilizes a user ratio parameter that plays a trade-off between system throughput, fairness and user throughput based on different channel conditions. Work on RA and power control to alleviate the effect of interference in device-to-device (D2D) communications in LTE-A uplink networks is outlined in [28]. RA and power control in SC-FDMA targeting minimum sum-power while satisfying users' QoS requirements is presented in [29]. Power allocation method for both localized and interleaved SC-FDMA is then offered. SC-FDMA femtocell based LTE-A uplink network with FUE admission and interference aware RA is discussed [30]. Joint admission control and RA algorithm and heuristic algorithm are employed to solve the developed optimization problem.

These works highlight advancements from other LTE applications. A group based uplink RA in M2M LTE-A communication is explored in [31]. In this scenario, group leaders facilitate the RA process for members that have data to transmit. In [32], IoT on LTE network is utilized as a backhaul for IoT based communication and RA algorithm to improve data rate and lower latency is outlined. Research on various security issues concerning LTE and LTE-A networks is undertaken in [33].

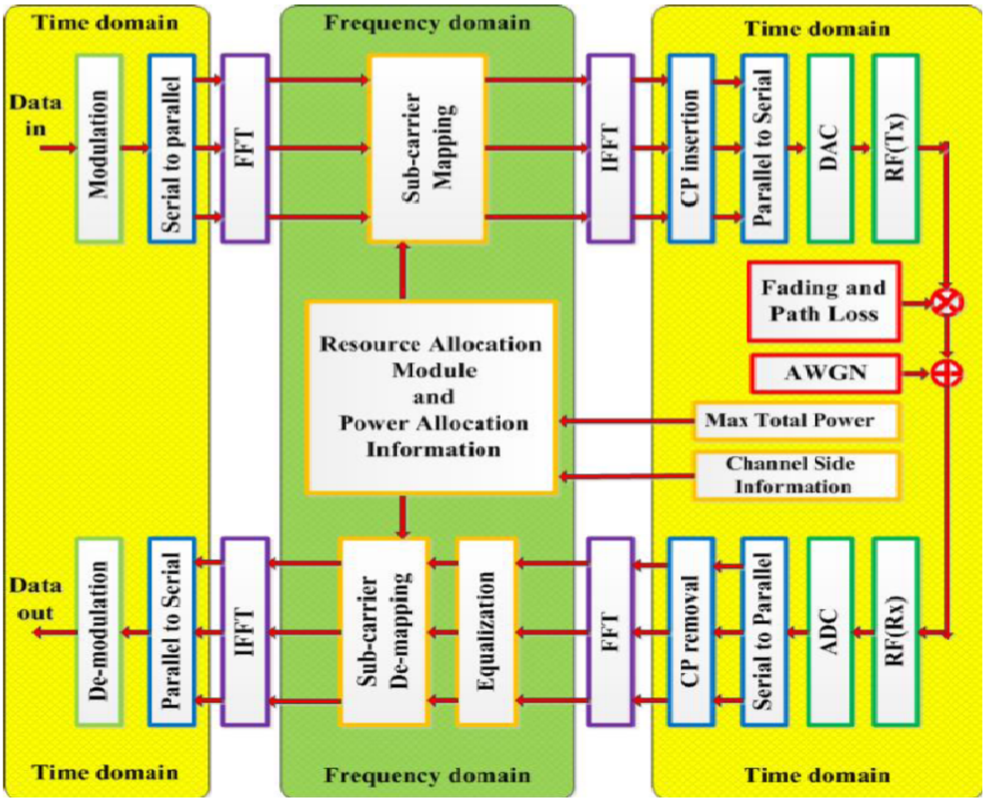

Fig. 3: 4G SC-FDMA architecture [23]

Challenges with respect to security vulnerabilities existent in architecture and design of LTE/LTE-A networks are identified and solutions reviewed. The performance of cooperative LTE-A networks regarding achievable rate in assigned subcarriers and power allocation is evaluated in [34]. A two-step technique that determines the data rate and then allocates power among subcarriers is implemented. QoS constrained RA scheduling for an LTE SC-FDMA system is outlined in [35]. Different scheduling approaches aimed at enhancing system throughput are discussed.

Uplink channel and buffer-aware RA algorithm for application in multi-cell LTE-A network is designed in [36]. Joint subcarrier and power allocation algorithms for SC-FDMA based femtocell networks is derived in [37]. The optimization problem is formulated with respect to cross-tier interference, FUE data rate requirements and SC-FDMA constraints. A low complexity sub-optimal algorithm for subcarrier allocation is then proposed. A study of energy efficient power allocation considering QoS constraints is done in [38]. After formulating the EE maximization problem, it is solved using a chaotic particle swarm optimization (CPSO) algorithm. The modification of these approaches is used in this work.

3.3 4G Challenges and Mitigation approaches

One of the challenges of 4G networks as identified in [39] is integrating non-IP based and IP based devices on a single platform and ensuring satisfactory QoS for user applications. Compared to the previous generations of technologies, there is increasing complexity in infrastructure concerning the need for multi-mode end-user terminals with corresponding complexity increases in billing systems due to the heterogeneous nature of 4G networks [40]. There are also concerns regarding the implementation of security issues to ensure users' information is protected [41]. The inter-connectivity and inter-working involved in 4G networks increases their vulnerability. There is a possibility of incompatible roaming frequencies which may occur as a result of different countries using different spectrum for 4G applications [42]. Congestion control presents a crucial issue in 4G networks necessitating the implementation of intelligent admission control and scheduling methods [40]. In order to access 4G services, multi-mode user terminals must choose their desired wireless system. The selection process is, however, complicated in 4G heterogeneous networks due to differences in wireless technologies and access protocols [43]. In summary, capacity improvement is the main challenge. Common mitigation approaches involve utilizing software defined radio technologies to scan for available networks. Radio resource allocation and packet scheduling strategies are crucial in enhancing the performance of OFDMA networks [44]. Works outlining how RA improves OFDMA performance are subsequently discussed. In [44], energy-efficient random access procedures and MAC protocols in LTE are also identified as one of the vital strategies of reducing random access overload that can result in high collision probability and energy wasting. A combination of network and user-oriented quality of experience (QoE) optimization approaches is recognized as a promising strategy to tackle QoE issues present in LTE networks. The high capacity requirements in recent wireless communication networks necessitate a shift towards 5G deployments involving improved access techniques and RA methodologies.

4 Fifth generation (5G) networks

This work mainly focuses on the capacity improvement of 5G networks through architectural changes and protocol improvements. These are presented next.

4.1 5G Architecture

There are diligent efforts from network operators to improve the digital landscape by addressing challenges such as increasing network capacity, energy efficiency, spectrum utilization as well as offering better scalability for a larger number of connected devices to service the constantly increasing mobile data traffic [8]. Stemming from expected trends of user demands in the 5G system, the IMT-2020 has identified the following broad categories that need to be supported [45].

1. *Enhanced Mobile Broadband (eMBB)*: To provide for enhanced bandwidth, wide-area coverage, spectral efficiency and signal efficiency in comparison to 4G, the 3GPP has definmed eMBB as one of the fundamental use cases for the 5G New Radio (NR) [46].

2. *Ultra reliable and low latency communications (URLLC)*: The 5G system will be applicable in mission critical activities such as autonomous driving, emergency services and remote control that need very low latency requirements. URLLC enables support for stringent latency requirements (typically in the range of 1ms) for mission critical activities [47].

3. *massive Machine Type Communication (mMTC)*: mMTC are realized through automatic data communication between intelligent devices with minimal human interaction. mMTC deployment will, however, face challenges of high numbers of devices with non-delay sensitive data. The diversity of mMTC devices will yield a wide range of data traffic patterns which will put further strain on already constrained spectrum thus making spectrum resource allocation an uphill exercise [48].

In [49], a two-tier 5G network architecture composed of a radio access network (RAN) and network cloud is illustrated. The network consists of technologies such as massive MIMO, network function virtualization (NVF), software defined networks (SDNs) and small cells that enable optimized network resource utilization for enhanced user quality of experience (QoE). Figure 4 depicts the implementation of this concepts in a typical 5G network. The feasibility of the recommended architecture is validated through a proof of concept which is outlined in the work, and important issues and challenges encountered for 5G implementation discussed. In [50], an SDN based network is proposed to provide a simplified and unified approach for routing management and mobility in 5G networks. The characteristics of 5G networks on which this work focuses is presented next.

4.2 Macrocell-Small cell networks

The high quality of service (QoS) requirements expected from cellular networks influenced by the need for high data rate, low latency and massive connectivity has motivated the concept of cell densification. The deployment of small cells in cellular networks can help increase throughput and capacity. Not only do small cells enhance signal reception indoors enabling high quality of service for various user applications but also facilitates frequency reuse between macrocells and femtocells resulting in improved network capacity and revenue for the operator [1]. Considering the increased

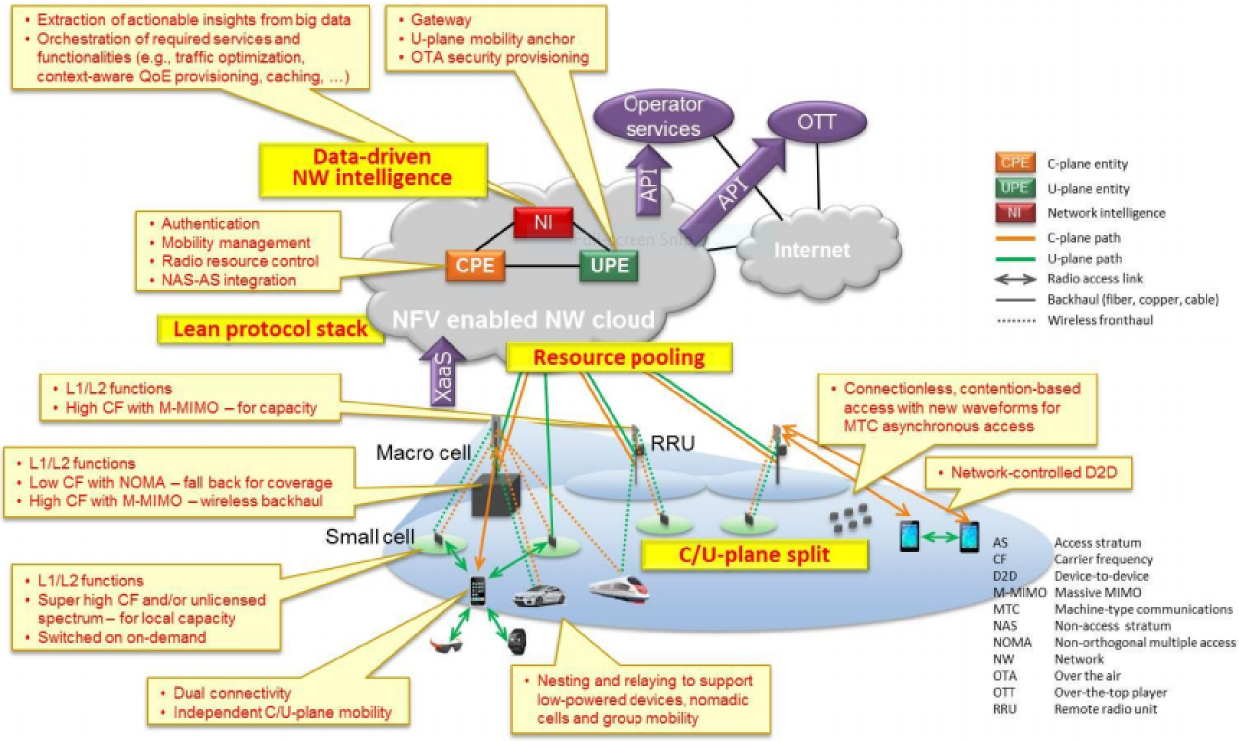

Fig. 4: 5G architecture [49]

pressure on limited radio resources and the costly utilization of more bandwidth [51], the deployment of heterogeneous networks (HetNets) consisting of macrocells and smalls has emerged as an appealing solution as it enables small cell base stations to be adjacent to mobile user devices. It is common practice to set up small cells in indoor environments allowing offloading of indoor user traffic and facilitating outdoor traffic to small cells. This enables HetNets to have seamless handover and smart offloading that increases overall spatial reuse [51]. High performance HetNets can be built using dense small cells of various sizes and macro base stations (MBSs). In [52], a small cell network for internet of things (IoTs) applications in 5G systems is developed. The network consists of small cell base stations that can switch on/off depending on the traffic load. Small cells are aimed at enhancing cellphones indoor performance given that an estimated 80% of cellphone calls transpire in offices, hotels, mall and homes [53].

4.2.1 Macrocell Networks

The implementation of early cellular networks featured the deployment of macrocells providing radio access in long range (km) scenarios. Macrocells can offer broad coverage and are often characterized by antenna masts that are ground-based or erected on rooftops and other structures. Macrocell users are serviced by an MBS. The MBS usually transmits at high power (in the order of 10W) compared small cell base stations. Enhancing the efficiency of the transceiver can significantly improve the performance of users in the macrocell.

4.2.2 Microcell Networks

Microcells provide and extend coverage for low-cost devices operating on GSM networks . An investigation of the performance of spectral efficiency in a macrocell-microcell network with respect to signal-to-interference and spectral efficiency is outline in [54]. As microcells are introduced to the macrocell environment a study of the impact of reuse factors is conducted. Research on the deployment of urban microcells (UMi) and urban macrocells (UMa) for 5G systems operating in 6 GHz to 100 GHz is presented in [55]. Wireless channel specifications such as path loss, shadow fading and blockage modelling of both UMi and UMa are described.

4.2.3 Picocell Networks

With a motive of improving system capacity, one of the effective methods is to implement efficient frequency reuse by sectioning the macro-cell into numerous small cells such as pico-cells. In Macro-Picocell networks, Pico eNBs are deployed inside the coverage of Macro eNBs. Different cases in which imbalances between macrocells and picocells are considered in [56] and the performance of cell selection methods that overcome the challenges evaluated. Additional cell selection algorithms that employ load-driven control to determine optimal user association are developed in [57]. Picocells can be deployed indoor or outdoor to offer improved coverage in residential and urban areas. Specific details regarding output power and cell radii are described in Table 1.

Table 1: Evolution of small cells [53]

Licensed Small-Cells				
	Femto	Pico	Micro/Metro	Macro
Indoor/Outdoor	Indoor	Indoor/Outdoor	Outdoor	Outdoor
Number of users	4 to 16	32 to 100	200	200 to 1000+
Max. output power	20 to 100mW	250mW	2 to 10W	40 to 100W
Max. cell radius	10 to 50m	200m	2km	10 to 40km
Bandwidth	10MHz	20 MHz	20,40MHz	60 to 75 MHz
Technology	3G/4G/Wi-Fi	3G/4G/Wi-Fi	3G/4G/Wi-Fi	3G/4G
MIMO	2×2	2×2	4×4	4×4
Backhaul	DSL,fiber	Microwave,mm	Fiber,microwave	Fiber,microwave

4.2.4 Femtocell Networks

Femtocells are the smallest denomination of small cells in wireless communication networks. Femtocell implementation is customer-friendly and can be easily installed by end users making them convenient low cost solutions to tackling the problem of poor coverage indoors [1]. Fibre optic or digital subscriber line (DSL) links serve as connections to femtocells [58] . Not only do subscribers enjoy benefits in terms of enhanced signal quality, power efficiency and throughput but also network operators have increased spectral efficiency and network capacity [59]. Resource management is highlighted as a vital aspect in maximizing throughput while preserving fairness among femto user equipments (FUEs) in LTE femtocell networks [60]. A packet scheduling scheme is proposed in the study which aims to achieve optimized aggregate throughput and average throughput among UEs. An approach to manage interference for uplink femtocell-macrocell networks using power control is outlined in [61]. Considering a multicell setup consisting of macrocells overlaid with femtocells, a demonstration of how power control can be used to minimize different types of interference in the system is presented. Interference can be very challenging in two-tier macrocell-femtocell networks. The nature of the two main types of interference that usually arises in two-tier networks is cross-tier interference and co-tier interference. An analysis of interference in downlink femto-macrocell network is done in [62]. An architecture that adopts interference based RA algorithms aimed at maximizing the throughput of the network is proposed. The implementation of femtocells in macrocells necessitates efficient frequency planning to mitigate the effect of interference between network layers. A dynamic frequency reuse technique is developed in [63] to minimize interference in femtocell-macrocell networks. The method reuses the spectrum of adjacent macrocells to protect femtocell users especially those at the cell edge. Dynamic spectrum assignment involving cognitive radio (CR) based approaches to effectively reuse macrocell radio frequency (CF) resources for indoor femtocells is outlined in [64]. It is proposed that the developed interference management can have cost efficient benefits for operators.

There are different types of access control in femtocells as identified [65];

- **Closed Subscriber Group (CSP):** In this mode, only subscribers are able to get access to femtocell resources.
- **Open Access:** In this scenario, all users are permitted to access femtocell services. Macrocell users passing by can thus acquire femtocell access.
- **Hybrid Access:** In this model, particular resources are reserved for registered subscribers while a certain level of open access is also granted for all users.

The characteristics of the cellular structures are summarized in table 1. The utilization of small cells in macrocells is one of the methods used to increase capacity in the network models developed in this work.

4.3 NOMA Access Schemes

4.3.1 Power Domain Non-orthogonal Multiple Access (PD-NOMA)

Power domain NOMA is recognized as the basic access method that exploits different power levels of users in the network (resulting from power control or naturally) to separate them [66]. It employs successive interference cancellation (SIC) to iteratively subtract and decode higher power signals from the superposition encoded signal while treating other embedded signals as noise. The fundamental principles under-laying power-domain NOMA techniques are studied in [67] with figure 5 illustrating application of SIC to derive users signals. The performance of integrating PD-NOMA with other well-established wireless communication methodologies such as multiple input multiple output (MIMO), cooperative communication, power allocation, etc. is examined. A power domain cyclic spread multiple access (PDCSMA) is designed for a NOMA system in [68]. Superposition coding (SC) and cyclic spreading applied at the transmitter is combined with symbol level SIC at the receiver to improve system BER. The advantages of PD-NOMA are that it accomplishes high spectral efficiency by serving multiple users on same time and frequency resources, and is able to mitigate interference using SIC. However, disadvantages of PD-NOMA come with the additional decoding complexity (compared to OMA systems) and possibility of errors rippling through the decoding process if one user makes an error [69].

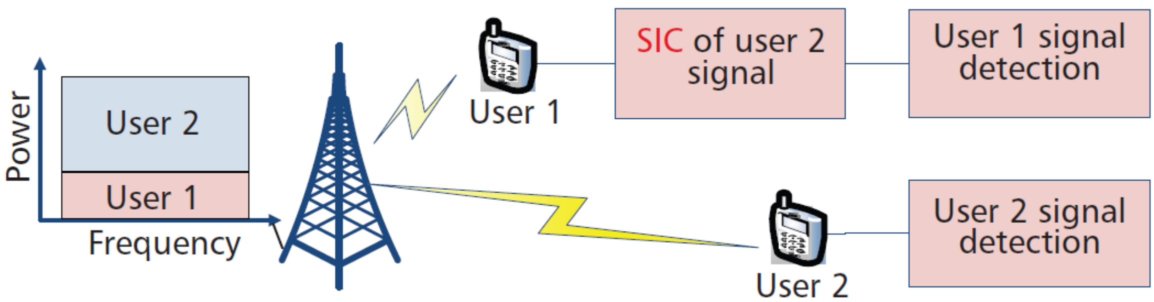

Fig. 5: PD-NOMA transceiver model [70]

4.3.2 Multi-User Shared Access (MUSA)

MUSA is a potential non-orthogonal transmission scheme with grant-free access for 5G mobile communication systems employing both code-domain and power-domain techniques in its operation [71]. Work considering MUSA for IoT applications is outlined in [72].MUSA embraces a grant-free strategy that provides access using both power domain and code domain methods. Complex short length sequences that enable massive connectivity at minimum control signal overhead and power consumption are applied to each user's data [72], [73]. An example of the application of MUSA spreading and SIC in a MUSA transceiver is illustrated in figure 6. Each user's data is spread using complex spreading codes that not only facilitate massive connectivity but also help minimize power consumption and signalling overhead for users in the same RB [71], [73]. MUSA utilizes blind detection based minimum mean square error successive interference cancellation (MMSE-SIC) to reduce the challenge of interference between users. MUSA's superiority compared to other NOMA access schemes is empowered by its high overloading,grant-free transmission and vigorous blind detection approach. The probability of spreading sequence collision is minimized by the vast number of available spreading sequences. MUSA, however, suffers from performance degradation due to propagation errors resulting from the application of SIC [71]. There is increased weight on the importance of designing spreading sequences as it is significant in reducing interference among users.

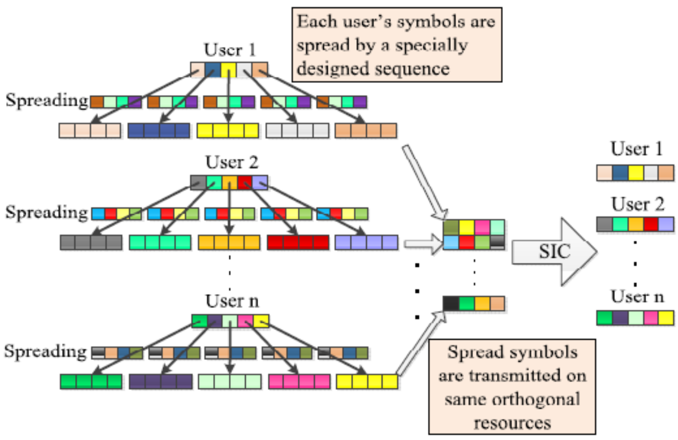

Fig. 6: MUSA transceiver model [73]

4.3.3 Interleaved Based NOMA (IDMA)

Introduced in [74], the IDMA NOMA scheme enables massive connectivity for users. The fundamental construct governing IDMA is the application of a combination of user-specific interleavers and low-rate channel coding as demonstrated in figure 7. The fundamental idea behind IDMA is utilizing interleavers for each user in combination with low-rate channel coding as seen in figure 7. As a wideband scheme it supports implementation of medium complexity multi-user detectors [75]. IDMA is derived from CDMA and possesses attractive CDMA traits such as diversity against fading as well as mitigation to user interference from neighboring cells [76]. IDMA is desirable for its high overloading and high spectral efficiency capability. As identified in [77], some of the advantages of IDMA are summarized as:

– IDMA enables iterative low cost methods for multi-user detection (MUD).

– Power controlled IDMA achieves near capacity multi-user sum-rate.

– Decentralized power control IDMA offers reasonably higher throughput compared to conventional ALOHA in random access scenarios.

– Data aided channel estimation (DACE) coupled IDMA can exploit massive multiple input multiple output (MIMO) systems.

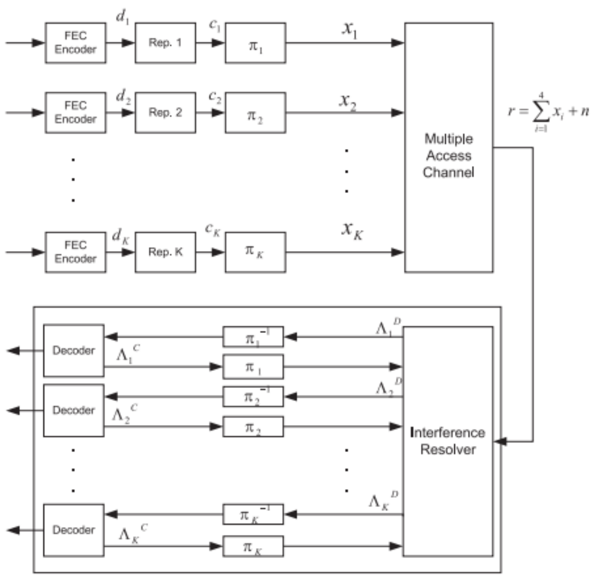

Fig. 7: IDMA transceiver model [75]

4.3.4 Pattern Division Multiple Access (PDMA)

The PDMA 5G NOMA access scheme developed in [78] introduces a technique of employing PDMA patterns for mapping user data to a resource pool composed of time, frequency, spatial resources or their various combinations. The designed PDMA patterns serve to not only distinguish user signals using common resources but also to enhance system performance with reasonable detection complexity. The multiplexing of users on same resource elements(REs) is illustrated in figure 8. As observed in the figure, RE3 has been allocated to users 1, 2,3 and 5. The performance of PDMA in downlink fully loaded wireless network is evaluated in [79]. PDMA with SIC is proposed to improve both spectral efficiency and system throughput subject to challenges such as novel multiple access (NMA) receiver and power allocation. The joint design of transmitter and receiver in PDMA enables low-complexity SIC based multi-user detection to be developed. PDMA patterns are designed for different users to achieve diversity disparity at symbol level and power disparity at resource element level [80]. An investigation of the outage performance and sum-rate of uplink PDMA system is undertaken in [81]. A case of three users sharing two resource blocks (RBs) is considered, and closed form expressions for outage probability and sum-rate are developed. A study of PDMA massive machine type communications (mMTC) grant-free(GF) transmissions is done in [82]. The performance of the proposed GF-PDMA is evaluated in terms of uplink resource allocation.

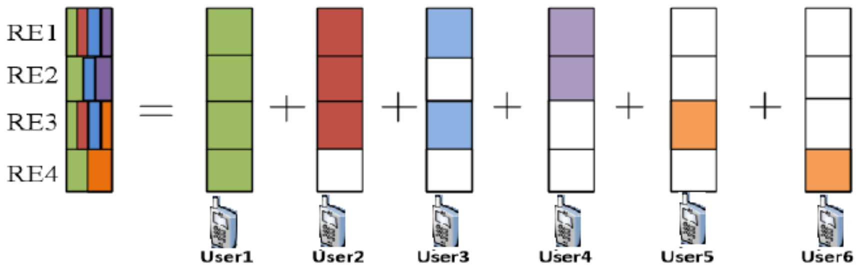

Fig. 8: PDMA transceiver model [78]

4.3.5 Sparse Code Multiple Access (SCMA)

Sparse code multiple access (SCMA) is an enhanced low density signature (LDS) method following the basic principles of CDMA employing low density spreading sequences [83]. SCMA enables the combination of QAM symbol mapping and spreading by using multi-dimensional codewords in SCMA codebooks. The SCMA encoding process that maps REs to codebooks is demonstrated in figure 9. SCMA employs multidimensional constellations to minimize collisions and receiver complexity to enable massive connectivity. The encoder in figure 9 implements mapping of resource elements to users through codebooks with message passing algorithm (MPA) being used at the receiver to decode transmitted data [84]. In addition to reducing detection complexity, codebooks used in SCMA map input coded bits using multi-dimensional modulation that helps introduce shaping gain which is one of the major advantages of SCMA. One of the disadvantages of SCMA is high detection and decoding complexity that increases with increasing number of users and larger constellations [71]. Studies on SCMA have been carried out in the following works. In [85], slight modifications to SCMA decoding are implemented to the deterministic message passing algorithm (DMPA) to improve performance and convergence. Hardware architectures based on Max-log MPA are discussed with timing and folding techniques proposed. Message passing algorithm (MPA) is often used to achieve low complexity decoding of sparse codewords at the receiver of SCMA. In [86], additional complexity reduction approaches are developed to decrease SCMA decoding complexity. Both transmitter SCMA codebook design and corresponding low complexity decoding methods are proposed. Another low complexity detection design aimed at decreasing computational complexity by combining adaptive Gaussian approximation and mean and variance feedback schemes is studied in [87]. The application of stochastic computing in designing low complexity SCMA detectors is investigated in [88]. The process of designing SCMA codebooks using permutations is outlined in [89]. The proposed system entails converting the considered codebooks into multi-user CDMA and then using an iterative decoder. A downlink multidimensional SCMA codebook design technique based on constellation rotation and interleaving in presented in [90]. Different codebook designs for power or spectral efficiency are generated and shown to have superior BER performance to existing downlink SCMA codebooks. Iterative multi-user receivers for uplink SCMA taking advantage of diversity and coding gains are developed in [91].

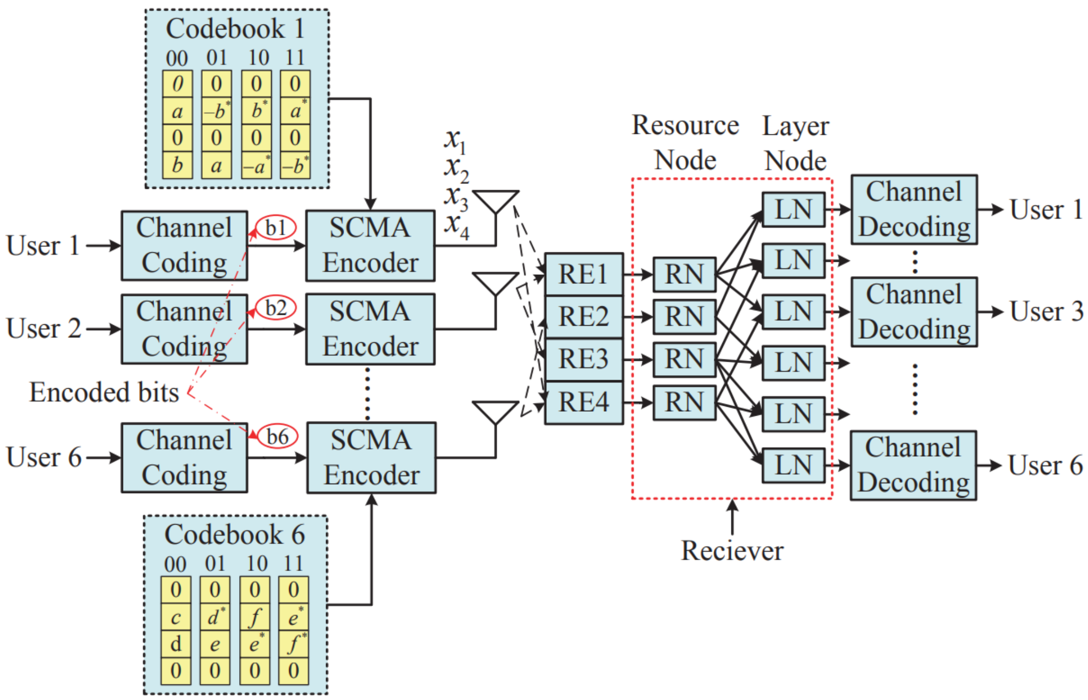

Fig. 9: SCMA encoding with K=6,N=4, J=2 [84]

In [92], the NOMA concept aimed at enhancing radio resource management for future radio access (FRA) in the 2020s and beyond is outlined. A basic NOMA downlink system employing successive interference cancellation (SIC) is investigated. A study of receiver and resource allocation optimization for uplink NOMA 5G networks is done in [93]. The derived method involves both applying iterative multi-user detection and decoding and subcarrier and power allocation algorithms to maximize users' sum-rate. Resource allocation for uplink power domain NOMA (PD-NOMA) is undertaken in [94]. The developed optimization problem is solved using many-to-many matching algorithm with additional iterative water-filling and geometric programming employed for power allocation. Cloud radio access network (C-RAN) represents an important network architecture as it enables central processing. An efficient RA technique for downlink NOMA C-RAN systems is presented in [95]. A sub-optimal user-pairing and power allocation algorithm is then applied to derive optimization solutions. The architecture of a typical 5G network is illustrated in figure 4 whereby a HetNet consisting of macrocells and small-cells with advanced MAC protocols are considered to increase network capacity.

4.4 5G Challenges and mitigation strategies

5G networks were standardized in 2018 and deployments expected to be rolled out in 2020 [45]. In their drive to achieve increased throughput, low-latency and high spectral efficiency, operators encounter major challenges due to interference, spectrum scarcity and increased energy consumption in 5G network deployment. A thorough review of the challenges and mitigation strategies is found in [96] [97]. The challenges addressed by this work are emphasized next.

4.4.1 Interference

In heterogeneous networks (HetNets) two common types of interference are usually identified namely cross-tier and co-tier interference. Cross-tier interference exists between users in different network layers while co-tier (which may consist of inter and intra small-cell interference) interference occurs among users in same network layer [98]. One of the major challenges in HetNets is inter-cell interference [99]. This problem is exacerbated by unplanned deployment of small cells where operators possess limited control on small cells' location. Different types of interference existent in HetNets are illustrated in figure 10. Table 2 below outlines different instances of interference that occur in two-tier HetNets as well as their dynamics. Interference in wireless networks is a constraint to capacity and needs to be minimized through application of effective MAC protocols.

4.4.2 Spectrum Scarcity

With the advent of the fourth industrial revolution which will be characterized by extensive applications of internet of things (IoT) and new 5G use cases, the already strained spectrum is going to experience more pressure. In an attempt to service the ever-increasing data demands from mobile users, there has been a growing trend in large-scale deployments of low power small cells overlaid in macrocells to address the issue of spectrum scarcity [100]. Spectrum optimization in dense

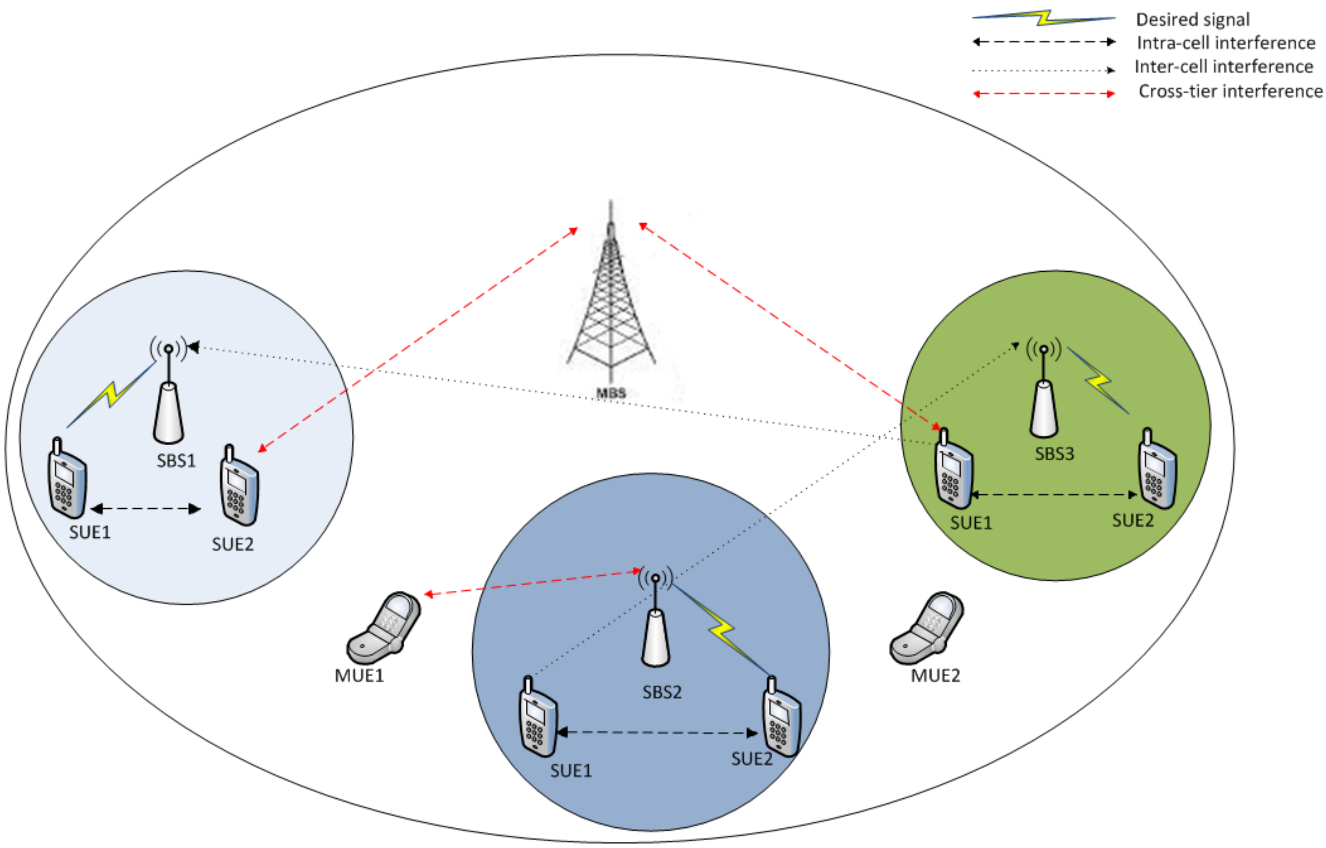

Fig. 10: Nature of interference in heterogeneous wireless networks

Table 2: Different cases of interference in HetNets [53]

Agressors	Victims	Interference type	Trasmission mode
MBS	small-cell UE	Cross-tier interference	Downlink
macrocell UE (MUE)	SBS	Cross-tier interference	Uplink
SBS	MUE	Cross-tier interference	Downlink
SUE	MBS	Cross-tier interference	Downlink
SBS	SUE	Co-tier interference	Downlink
SUE	SBS	Co-tier interference	Uplink
SUE	SUE	Intra-cell interference	Uplink/Downlink

heterogeneous networks requires efficient resource scheduling and interference management [101], [102], sum-rate maximization [103], [104] and high spectral efficiency [105]. Massive MIMO is expected to add pressure on already strained spectrum. Although massive MIMO has been proposed to offer diversity and compensate effects of path loss in 5G networks [106].

4.4.3 Heterogeneous Networks (HetNets)

To address the challenge of high data demand from users, HetNets which consist of macrocells overlaid with small cells is envisioned to be a promising solution to relieve pressure on limited spectrum resources [100]. Work considering dynamic RA in hybrid automatic repeat and request (HARQ) is done in [107]. Mathematical models for analyzing throughput and developing distributed RA policies in donwlink and uplink HetNets are presented. Theoretical formulations of multi-tier networks assuming random spatial models is constructed in [108] with practical performance constraints possible challenges that restrict operators in maximizing network capacity also outlined. Software defined networks (SDN) have been proven to have promising potential in enhancing 5G performance. However, there is still need to advance SDN concepts such that they can be applicable at network infrastructure level (e.g. carrier network). Development of unified cellular programmable interface to enable SDN infrastructure implementation and establishing global standardization are other challenges facing SDNs [99].

4.4.4 Energy Efficiency

Due to the meteoric increase in popularity of smart devices that require high capacity from access fourth and fifth generation networks, the energy demand from recharging such devices has been become significant [109]. Therefore, research interests in energy efficiency (EE) studies have increased in recent years. QoS based EE consideration for uplink LTE networks in machine-to-machine (M2M) or human-to-human (H2H) instances is studied in [110]. After formulating the EE optimization problem, it is transformed into a mixed integer problem (MIP) which is then solved using canonical duality method. Optimization of energy efficiency in uplink SC-FDMA is considered in [111]. A low complexity optimal power allocation algorithm to maximize EE is presented and its performance compared to conventional power allocation methods. A study on efficiency and fairness scheduling in resource allocation for uplink SC-FDMA is conducted in [112]. Various frequency domain packed schedulers with fairness, transmit power, price of fairness as performance metrics are described. Efforts to maximize energy efficiency RA in downlink NOMA by implementing subcarrier and power allocation is presented in [113]. Sub-optimal matching subchannel allocation algorithms that solve the optimization problem are proposed. Energy efficiency optimization is considered for a NOMA downlink system in [114]. The resulting non-convex optimization problem is solved using a difference of two convex functions (DC) approach. Power allocation methods for NOMA multicast-unicast systems involving different cognitive radio NOMA (CR-NOMA) technologies are designed in [115]. The approaches are evaluated in terms of outage probability. After considering challenges and the existing mitigation approaches in literature, the following research problem is formulated and objectives and methodology subsequently outlined.

5 Research Problem Formulation and Motivation

Recent wireless communication networks such as the fourth (4G) and fifth (5G) generation networks are expected to meet particular minimum requirements in terms of quality of service (QoS). There is need to improve network capacity by developing MAC protocols with better performance, by implementing heterogeneous networks (consisting of macro and small cells) with increased capacity, and applying more efficient resource allocation algorithms based on modern artificial intelligence (e.g. nature inspired algorithms). The developed schemes should aim at alleviating existing wireless communication environment challenges such as interference and spectrum efficiency. Biologically inspired computational algorithms have been proven in a myriad of engineering applications to offer satisfactory solutions within reasonable execution time. Motivated by this perspective, this work seeks to answer the following questions. Can we develop hybrid network architectures that can improve capacity? Can we apply multiple MAC protocols on the models and finally can biologically inspired algorithms be applied to improve capacity?

6 Research Objectives

The following identified objectives are the focus of this thesis:

1. To provide a detailed critical literature review of LTE-A and NOMA technologies.
2. To develop and investigate a HetNet model based on LTE-A and evaluate the performance of nature-inspired algorithms solutions based on particle swarm optimization (PSO) ant colony optimization (ACO), and a developed hybrid algorithm embracing the merits of PSO and ACO referred to as Adaptive Particle Ant Swarm Optimization (APASO) for resource allocation in uplink LTE-A (SC-FDMA).
3. To develop and investigate a hybrid NOMA HetNet model based on PD-NOMA and SCMA and evaluate the performance of proposed RA biological algorithms namely particle swarm optimization (PSO) ant colony optimization (ACO), and a developed hybrid algorithm embracing the merits of PSO and ACO termed Adaptive Particle Ant Swarm Optimization (APASO).

7 Research Methodology

This work contributes to knowledge by considering the application of metaheuristic and analytical optimization tools, apart from MATLAB simulations. Nature-inspired metaheuristic approaches studied are particle swarm optimization (PSO), ant colony optimization (ACO) and the proposed adaptive particle ant swarm optimization (APASO). Analytical methods based on convex optimization and Lagrangian dual technique are utilized to compare the performance of the biological algorithms. The energy efficiency optimization problem is formulated and solved first using the biological methods whose performance is subsequently compared to the well-established convex optimization approximation approach. The analytical tools and algorithms used in the methodology are discussed in detail next.

The considered optimization methods are termed as metaheuristic algorithms. “Meta-" is a Greek word that means “beyond" or “higher", and “heuristic" describes a class of stochastic algorithms used to solve optimization problems although not always guaranteeing best solutions at all applications [116]. Metaheuristic algorithms often perform better as compared to simple heuristics [117]. Inspired by natural processes, metaheuristics are characterized by having diversification and intensification as two fundamental phases in their operation. Diversification involves random exploration of the search space to discover good quality solutions to the optimization problem, while intensification is the exploitation of the obtained solutions. The balance between exploration and exploitation is crucial in the satisfactory performance of metaheuristic algorithms. Hence they were found favourable and applied in this work. Metaheuristics can be categorized into population-based and trajectory-based algorithms. Examples of population-based algorithms are genetic algorithm (GA), particle swarm optimization (PSO), ant colony optimization (ACO). A good example of a trajectory-based algorithm is simulated annealing (SA) [116].

7.1 PSO

Preliminary studies relating to the behavior of flocks or herds of animals hunting for food were considered in the Boid’s Model [118]. Drawing on this inspiration, the particle swarm optimization (PSO) search technique was developed. PSO is based on the behavior of a flock of birds or a school of fish searching for food in nature. Initially proposed by [119] it models potential random solutions as a swarm of particles. Each particle in the swarm has a position and a velocity. In searching for better solutions each particle iteratively updates its previously best fitness position and adjusts its velocity in the direction of its personal best and that of the best particle in the swarm (global best). The advantages of PSO reside in its simple implementation that requires few parameters to adjust while sustaining robustness, fast convergence and short computational times. It can also be efficient in obtaining solutions to problems that pose difficulty to solve using accurate mathematical approaches. Nonetheless, PSO might not be suitable to scattering problems and can have premature convergence or be trapped in local minimum in complex problems cases [120]. The potential of PSO to be able to derive near-optimal solutions for NP-hard problems is the reason why it was considered for this study.

7.1.1 Principle of operation

PSO utilizes a swarm of particles travelling through a multi-dimensional search space. Let $p_{ij}(t)$ and $v_{ij}(t)$ be the position and velocity vectors of the i^{th} particle in the j^{th} dimension at time t. Then a PSO algorithm that governs particle in d-dimensional is updated according to the following velocity and position equations as described in [119], [121]

$$v_{ij}^{t+1} = \omega v_{ij}^{t} + r_1^t C_1 (p_{ij}^{best,t} - p_{ij}) + r_2^t C_2 (p_{ij}^{global,t} - p_{ij}), \tag{1}$$

$$p_{ij}^{t+1} = p_{ij}^{t} + v_{ij}^{t+1}. \tag{2}$$

The variables $p_{ij}^{best,t}$ and $p_{ij}^{global,t}$ in (1) represent the personal and global best positions, ω is referred to as the *inertia* of the particle, r_1 and r_2 are random variables in the range $0 \leq r_1, r_2 \leq 1$, while C_1 and C_2 are cognition and social acceleration coefficients respectively. Parameter selection and conditions relating to the convergence of the PSO algorithm are investigated in [122].

7.1.2 Description of PSO algorithm parameters

1. *Fitness function*: A particles often represents a solution to the optimization problem to be solved. Each particle is evaluated using a fitness function which is associated to the optimization problem. A fitness value is then assigned to each particle to ascertain the suitability of the particle to solving the problem. The aim is to select particles with high fitness values and to communicate these high fitness value positions to other members of the swarm such that the entire swarm evolves to better solutions.

2. *Position*: The position vector of the particle stores locations of feasible solutions in the search space [123]. The dimension of the position vector depends on the nature of the optimization problem under consideration. During its exploration each particle instantaneously updates its position according to equation (2).

3. *Velocity*: Particles move about in the search space with velocity, v_{ij}^t, in equation (1). The dimension of the velocity vector is equivalent to the position vector and is used to move particles towards personal best and global best values of the swarm.

4. *Personal best and Global best values*: Each particle stores its previously best personal fitness value and the highest fitness value in the entire swarm of particles is designated the global best of the swarm [124]. As the swarm flies over the search space, the personal and global values are updated if new values which are better than the stored values are discovered.

5. *Inertia* : Particles inertia weight factor is a key element in balancing the exploration and exploitation processes as particles move about the search space. Although the original PSO model did not have inertia incorporated in it, constant inertia was introduced in [125]. Further experiments involving various inertia updating strategies are outlined in [126].

6. *Social and Personal acceleration coefficients* : Social and personal 'learning' acceleration coefficients are weights that pull particles towards current personal and global best values of the swarm. Common practice in the implementation of the PSO is to strive for a trade-off between extremely high or low values of these coefficients [121]. Extremely high values usually cause sudden movements of particles which risk them being trapped in false optimal values while extremely low values of the coefficients result in high computational cost of the PSO.

7. *Random factors*: Randomness of the PSO algorithm is introduced via coefficients r_1^t and r_2^t in equation (1). These variables enable search space exploration and are often selected as uniform numbers in the range [0,1] [122].

7.1.3 Applications of PSO algorithm

A PSO approach for cloud based social applications to optimize QoS is presented [127]. The performance of the PSO is compared to that of the greedy algorithm regarding its RA efficiency. A PSO power allocation (PA) technique for downlink NOMA networks is considered in [128]. The developed PSO PA is aimed at maximizing energy efficiency in the network. Work on RA using PSO to improve Quality of Experience (QoE) while ensuring fairness among users in downlink LTE is done in [129]. The RA problem for different traffic classes is formulated in PSO framework and PSO performance compared to other throughput maximization algorithms. Joint mode selection and RA using PSO is explored in [130]. The fitness function of particles is constructed to provide solutions that maximize system throughput. PSO based RA for LTE device-to-device(D2D) communication intended to improve throughput is outlined in [131]. The performance of the proposed PSO in assigning resource blocks to users is compared to that of random allocation method. A PSO application for energy efficiency in 5G Network Base Stations is defined in [132]. Based on HetNet scenarios with separate data and control planes, PSO is employed to derive energy saving solutions for base stations. PSO based RA and scheduling in production management scenarios is illustrated in [133]. Different instances of how solutions are mapped to particles are presented.

7.2 ACO

The ant colony optimization (ACO) paradigm introduced by [134] is a cooperative search mechanism imitating the behavior of ants as they forage for food in nature. In the beginning ants search randomly in the environment to discover shortest routes between the food source and the nest. In routes in which they have discovered food, they leave pheromone trails for other ants to follow in future travels. The advantages of ACO are that it can yield satisfactory solutions due to its parallel search capability in the ant population. It has also guaranteed convergence. Nevertheless, its disadvantages are that the probability distribution of its solutions can change per iteration, and it has uncertain time to convergence [120]. The parallel search ACO characteristic that enables it to procure good solutions quickly is what made it attractive for application in this work.

7.2.1 Principle of operation

The ant colony optimization metaheuristic has popular applications in travelling salesman problems (TSP) and assignment type problems (ATP). In TSP scenarios, the interest is attempting to find the shortest path from the food source to the nest. In the TSP problem, the pheromone, τ_{ij}, on the path $i - j$ between nodes i and j is updated according to

$$\tau_{ij}(t+1) = \rho\tau_{ij} + \Delta\tau_{ij}, \tag{3}$$

where t is the number of iterations, ρ is the pheromone evaporation rate ($0 < \rho < 1$), $\Delta\tau_{ij}$ is the deposited pheromone on each iteration by each ant and is given by

$$\Delta\tau_{ij} = \sum_{a=1}^{m} \Delta\tau_{ij}^{a} \tag{4}$$

where m is the number of ants and

$$\Delta\tau_{ij}^{a} = p_a = \begin{cases} \frac{Q}{L_a}, if \quad the \quad a^{th} \quad ant \quad walks \quad on \quad edge(i,j) \\ 0, \text{otherwise}, \end{cases} \tag{5}$$

where Q is a constant and L_a is the length of tour of the a^{th} ant. The visibility or heuristic function in this case is defined as

$$\eta_{i,j} = \frac{1}{d_{i,j}}, \tag{6}$$

where $d_{i,j} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$. The probability, p_a^{ij}, of choosing a certain particular path,

$$p_a^{ij} = \begin{cases} \frac{[\tau_{ij}]^\alpha [\eta_{ij}]^\beta}{\sum_{a \in S_{ij}} [\tau_{ij}]^\alpha [\eta_{ij}]^\beta} \\ 0, \text{otherwise}, \end{cases} \tag{7}$$

where α, β are pheromone and heuristic function weights, S_{ij} is the set of possible routes. ACO has been applied in assignment type problems(ATP) in which each ant incrementally builds a solution by assigning tasks to agents subject to particular constraints [135]. In such scenarios, resource allocation is implemented in a manner that optimizes system performance. The pheromone mechanism provides a means of communication between ants regarding which tasks are suitable to which agents. Let the aggregate pheromone intensity of allocating task i to agent j be denoted as $\tau_{i,j}$. Assuming that $\eta_{i,j}$ is the heuristic value representing the desirability of assigning agent j to task i, then the probability, p_a, of ant a selecting task i for agent j is given by

$$p_a = \begin{cases} \frac{[\tau_{i,j}]^\alpha [\eta_{i,j}]^\beta}{\sum_{j \in J_a} [\tau_{i,j}]^\alpha [\eta_{i,j}]^\beta}, \\ 0, \text{otherwise}. \end{cases} \tag{8}$$

where α and β are pheromone and heuristic function weights, Ja is the set of available agents. The pheromone updating rule for choosing an agent to a task is updated as

$$\tau_{i,j} \leftarrow (1 - \rho) \cdot \tau_{i,j} + \rho \tau_o, \tag{9}$$

where τ_o is the initial pheromone concentration and ρ is the pheromone evaporation rate $(0 < \rho < 1)$.

7.2.2 Description of ACO algorithm parameters

1. *Fitness function* The fitness function is utilized to evaluate the efficiency of ants in deriving solutions to the optimization problem under consideration. Each path is assessed using the fitness function which is modelled using the problem to be solved and a fitness value is associated with each path. Since paths generated by ants as they walk about the search space are analogous to solutions to the optimization problem, paths with higher fitness values will be preferred as they represent better solutions to the problem.

2. *Pheromone updating rule*: As ants travel from the nest to food source searching for food they deposit a chemical called to as *pheromone* on the ground. The process of preromone trail-laying and trail-following serves as indirect communication referred to as “stigmergy" [136]. Ants communicate through modifications to the environment using pheromones for other ants to follow this trails to find the food source. In ACO problem solving applications, pheromone is laid on desirable solutions so that such solutions can be frequented more often as long as they yield satisfactory results.

3. *Heuristic Function*: Indicates the desirability of ants to chose particular destinations in their travels. Paths in which food sources are closer to the nest are more appealing to ants as they are more likely to have higher pheromone intensity.

4. *Probability rule* During their expeditions ants select paths to follow based on a probability rule(s). The probability rule is constituted by a combination of various factors such as local pheromone intensity and heuristic function values, ants memory based on its past trips and the nature of the problem [137].

7.2.3 Applications of ACO algorithm

An example of spectrum allocation based on ant colony optimization to a home area network in Internet of Things (IoTs) application is studied in [138]. The algorithm is employed to provide fair resource assignment in cloud based machine-to-machine communication. ACO RA in cloud computing environment is considered in [139]. An analysis of ACO in dynamic resource scheduling in cloud computing scenarios is then performed. ACO is investigated in terms of static and adaptive heuristic control to improve the quality of its solutions [135]. Applications in local search and component selection heuristics for generalized assignment problems are then considered. An improved ACO combining differential evolution and variable neighbourhood search processes is developed in [140] . It is applied in spectrum assignment RA instances of cognitive radio networks modelled using graph theory. ACO for RA and anomaly detection in communication networks is explored in [141]. Its performance is evaluated with respect to power control, throughput and convergence in CDMA networks, and analyzed in its efficiency for anomaly detection in computer networks. ACO is also utilized to derive quasi optimal solutions for circular consecutive k-out-of-n systems in [142].

7.3 Convex Optimization

Convex optimization has recently gained popularity in resource allocation applications in wireless communication and networking environments. Consider a standard convex optimization problem

$$\min_{x \in R \subseteq P} f(x), \tag{10}$$

where x is a vector that represents optimization variable, $f : P^n \rightarrow P$, P is a set of convex functions for minimization, R is a set of feasible solutions. Among the techniques of convex optimization the Lagrange dual principle is famous in wireless communication optimization problems. It involves the application of Lagrange multipliers and Karush-Kuhn-Tucker (KKT) conditions to establish optimality. In the Lagrange duality method the optimal solution of a dual problem under consideration is presented as a vector of KKT multipliers.

The Lagrange technique is employed to optimize the number of FUEs allocated spectrum resources with FUEs transmitting at optimal power. The EE optimization problem is developed and solved following fractional transformation [143]. Considering the joint user scheduling and power allocation in [144], an optimal RA strategy based on the Lagrange optimization model is defined as

$$\min_{x \in Z \subseteq P^n} f_q(x) \tag{11}$$

s.t.

$$g_q(x) \leq 0 \quad q = 1, 2, \ldots, r,$$

$$h_q(x) = 0 \quad q = 1, 2, \ldots, s,$$

where $f_q(x)$ is the objective function, g_q and $h_q(x)$ are inequality and equality constraints which are affine and x is the optimization variable. Solutions to equation (11) will provide values that minimize $f_q(x)$ for all values of (x) given $q = 1, 2, \ldots, r$ and $q = 1, 2, \ldots, s$ ∈Z.

Consider a convex optimization problem with constraints as outlined in equation (11), the Lagrangian function, $L(P^n \times P^r \times P^s)$, is given by

$$L(x, \lambda, \gamma) = f_0(x) + \sum_{q=1}^{r} \lambda_q g_q(x) + \sum_{q=1}^{s} \gamma_q h_q(x), \tag{12}$$

where $\lambda \in P^r$ and $\gamma \in P^s$ are optimization variables of λ_q and γ_q with $g_q(x)$ and $h_q(x)$ inequality and equality constraints respectively. These variables are often referred to as Lagrangian dual variables or simply Lagrange multipliers [145]. Lagrange multipliers that yield optimal values are denoted as p^* and correspond to the minimum value of the objective function

$$p^* = min\{f_0(x) : g_q(x) \leq 0, q = 1, 2, \ldots, r, h_q(x) = 1, 2, \ldots, s\}. \tag{13}$$

The vector variable is optimal if $f(x^*) = p^*$. It is possible to have more than one optimal point in the set of feasible solutions [146]

There have been studies conducted on the application of convex optimization for resource allocation in wireless communication networks. Work illustrating the application of convex optimization in RA in wireless communication networks is presented in [147]. It is demonstrated how RA functions that may not necessarily be concave can be solved using the dual domain framework. QoS and fairness based convex optimization RA for wireless cellular and Ad Hoc networks is proposed in [148]. Convex optimization formulations are a developed with a target to optimize the overall system throughput subject to constrains such as power, probability of outage and data rates. Further work detailing convex optimization based RA in multi-antenna systems is outlined in [149].

In this research MAC protocols are developed for both uplink 4G and 5G networks using HetNet models consisting of macrocells and small cells to increase capacity. RA based algorithms motivated by biological algorithms are implemented to enhance radio resource utilization. The following sections outline research contributions considering application of PSO, ACO and the developed hybrid algorithm Adaptive Particle Ant Swarm Optimization (APASO) embracing the merits of both PSO and ACO. The performance of the biological algorithms is compared to that of the analytical Lagrange method.

8 Research Main Contribution

The research has resulted into the following main papers.

Contributions of Papers

Paper A : Alternative Energy Efficient Resource Allocation Algorithms for Uplink LTE-A Networks, *under review*

Abstract:

Long Term Evolution Advanced (LTE-A) access technology employs Single Carrier Frequency Division Multiple Access (SC-FDMA) on the uplink to minimize power consumption. SC-FDMA technology requires special resource block allocation patterns due to the subcarrier adjacency and exclusivity restriction resulting in resource allocation problems. Unlike the traditional analytical combinatorial resource allocation schemes, this work proposes alternative biological inspired resource allocation schemes for SC-FDMA due to their advantages of simple implementation compared to other analytical methods. The performance of the developed schemes, Particle Swarm

Optimization (PSO), Ant Colony Optimization (ACO) and the proposed hybrid Adaptive Particle Ant Swarm Optimization (APASO), is investigated and compared to that of the analytical model based on Lagrangian optimization. The performance and complexity of the biological algorithms is observed to be near-optimal with APASO outperforming the traditional PSO and ACO algorithms in resource allocation.

Paper B: Biological Resource Allocation Algorithms for Heterogeneous Uplink PD-SCMA NOMA Networks, *In press*

Abstract

Due to their ability to multiplex users on a resource element (RE), Non-orthogonal multiple access (NOMA) techniques have gained popularity in 5G network implementation. The features of 5G heterogeneous networks have necessitated the development of hybrid NOMA schemes combining the merits of the individual NOMA schemes for optimal performance. The hybrid technologies on 5G networks make complex air interfaces resulting in new resource allocation (RA) and user pairing (UP) challenges aimed at limiting the multiplexed users interference. Furthermore, common analytical techniques for evaluating the performance of the schemes lead to unrealistic network performance bounds necessitating alternative schemes. This work explores the feasibility of a hybrid power domain sparse code non-orthogonal multiple access (PD-SCMA). The scheme integrates both power and code domain multiple access on an uplink network of small cell user equipments (SUEs) and macro cell user equipments (MUEs). Alternative biological RA/UP schemes; the ant colony optimization (ACO), particle swarm optimization (PSO) and a hybrid adaptive particle swarm optimization (APASO) algorithms, are proposed. The performance results indicates the developed APASO outperforming both the PSO and ACO in sum rate and energy efficiency optimization on application to the PD-SCMA based heterogeneous network.

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Part II

Included Papers

Paper A

Alternative Energy Efficient Resource Allocation Algorithms for Uplink LTE-A networks

Thabelang Sefako and Tom Walingo

1 Abstract

Long Term Evolution Advanced (LTE-A) access technology employs Single Carrier Frequency Division Multiple Access (SC-FDMA) on the uplink to minimize power consumption. SC-FDMA technology requires special resource block allocation patterns due to the subcarrier adjacency and exclusivity restriction resulting in resource allocation problems. Unlike the traditional analytical combinatorial resource allocation schemes, this work proposes alternative biological inspired resource allocation schemes for SC-FDMA due to their advantages of simple implementation compared to other analytical methods. The performance of the developed schemes, Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO) and the proposed hybrid Adaptive Particle Ant Swarm Optimization (APASO), is investigated and compared to that of the analytical model based on Lagrangian optimization. The performance and complexity of the biological algorithms is observed to be near-optimal with APASO outperforming the traditional PSO and ACO algorithms in resource allocation.

2 Introduction

The Long Term Evolution Advanced (LTE-A) access technology utilizes Orthogonal Frequency Division Multiple Access (OFDMA) on the downlink and Single Carrier Frequency Division Multiple Access (SC-FDMA) on the uplink for communication. SC-FDMA is employed on the uplink due to its ability to resist multipath fading and its low Peak Average Power Ratio (PAPR). Resource Blocks (RBs) in SC-FDMA are transmitted in a manner that results in lower Peak Average Power Ratio (PAPR) when compared to OFDMA. The lower PAPR makes mobile terminals more power efficient by reducing the battery power consumption of User Equipments (UEs). However, this comes at a cost of exclusivity and contiguity/subcarrier adjacency RB allocation restrictions [1]. The exclusive restriction, applicable to both downlink and uplink, requires one user assigned to one RB whereas in the subcarrier adjacency restriction users can only be assigned multiple subcarriers that are adjacent to each other. The LTE-A resource allocation (RA) constraints and challenges demand the development of efficient resource pattern allocation strategies hence the focus of this work.

Mathematical algorithms are commonly used for resource allocation in LTE-A networks. In [2] [3], [4], game theory has been implemented to solve the resource allocation problem modelled as a game in which UEs are represented as players and network resources are distributed according to

UE quality of service (QoS) requirements. When a Nash equilibrium is reached, the system is considered to be operating at optimum. These models are disadvantaged in their slow convergence to optimal solutions. Greedy algorithms have also been employed in resource allocation applications as they are easy to implement. At each instant in their execution, they choose a local optimum in the hope that selecting a local optimum at each step will result in an optimal solution to the optimization problem. However, greedy algorithms do not always reach global optimum solution. In most works, LTE-A uplink resource allocation problem is usually characterized as an NP-hard combinatorial optimization problem which is often formulated as a Binary Integer Problem (BIP). The benefits of defining the RA problem as a BIP is that it encapsulates SC-FDMA constraint requirements. The introduction of RB contiguity constraint in LTE-A uplink RA results in an NP-hard problem making exhaustive search for solutions computationally expensive. Most works have addressed the LTE-A SC-FDMA RA problem using Lagrange dual decomposition method. This often requires defining the Lagrange function and mathematically solving the RA optimization problem. The Lagrange dual decomposition has been proposed to offer optimal solutions although it is mathematically rigorous. One of the disadvantages of Lagrange optimization is that non-convex problems sometimes need to undergo relaxation to be converted into convex problems before optimization leading to approximate solutions.

Though rarely used in LTE-A resource allocation, biologically motivated algorithms based on natural behavior of organisms are suitable for alleviating the RA constraints and dynamism of LTE-A uplink. The adaptive nature of these biologically motivated algorithms can be suited to dynamic wireless environments. These meta-heuristic algorithms are simple to implement once potential optimization solutions can be encoded into the algorithms' respective framework. However, it might be challenging to model feasible solutions into meta-heuristic natural structures. Genetic algorithm (GA) [5] is based on Charles Darwin' natural selection theory in which good genes survive while bad ones are discarded by selection, crossover and mutation processes. In the application of GA in RB scheduling in LTE, RBs are represented as genes that build chromosomes which are feasible scheduling solutions to the optimization problem. Ant Colony Optimization (ACO) [6] mimics the behavior of ants foraging for food in nature. Ants communicate indirectly with other ants in the colony using "stigmergy" whereby they leave a trail called pheromone for other ants to follow in order to find food. Potential solutions to optimization problem are represented as routes generated by ants as they travel in the seach space. The inherent parallelism and positive feedback characteristics of ACO are desirable for finding good solutions hence their choice of application in LTE-A resource allocation. However, random ant tours in the beginning of the algorithms can result in slow convergence. Motivated by the behavior of a flock of birds or a school of fish searching for food in nature, Particle Swarm Optimization (PSO) [7] is grounded on simple social interaction observations of birds. Birds search for food as a swarm and communicate locations of their previous findings with each other to maximize their exploration discoveries. In PSO, particles represent possible solutions to the problem under consideration. PSO algorithm is attractive in allocating resources in LTE-A networks due to its simple implementation and efficiency in solving continuous problems, hence its application. Our proposed hybrid Adaptive Particle Ant Swarm Optimization (APASO) harnesses the merits of both PSO and ACO to improve speed of convergence. This will save on computing resources, required by PSO and ACO, while achieving near optimal solutions. This work proposes the application of PSO, ACO and the developed hybrid APASO algorithm for LTE-A uplink RA. These methods have not been previously applied in literature for SC-FDMA resource scheduling. The performance of these methods is comparable to the approximate Langragian model that normally provides the upper bound [8] and can be prohibitively difficult to apply in certain RA scenarios for SC-FDMA [9], therefore alternative and simpler RA techniques need to be developed and is the motivation of this work.

The rest of the paper is organized as follows: Section 2 outlines related work on LTE uplink RA and previous hybridization applications of the above mentioned algorithms. Section 3 describes the system model to be adopted in the paper and how the RA problem is formulated. Section 4 formulates the LTE-A scheduling problem, followed by analytical Lagrangian solution of the problem under consideration and the application of alternative LTE-A uplink RA approaches. Section 5 shows performance evaluation results, and Section 6 concludes the paper.

3 Related Work

Mathematical algorithms have been used for resource allocation in wireless networks. A game theoretic model for resource allocation in multi-service SC-FDMA wireless networks is presented in [2]. A user-centric distributed non-cooperative multilateral bargaining model that entices users to select their preferred discount factors is developed. In [3], a buffer aware resource scheduling scheme that considers buffer size, channel condition, and packet delay in allocating frequency resources is proposed. It employs game theory to implement a negotiation mechanism in allocation of RBs between UEs depending on different UE QoS requirements. The authors in [4] consider game theory resource allocation for multi-service SC-FDMA. In [10] the authors present a unified graph labelling algorithm in which the channel allocation in SC-FDMA is modelled as an acyclic graph. Joint optimal chunk and power allocation in uplink SC-FDMA is conducted in [11] in which optimum resource chunk assignment is represented as maximum weighted matching problem on a bipartite graph. In [12] the authors develop low complexity channel dependent scheduling using greedy algorithm to increase sum-rate capacity of uplink SC-FDMA. The authors in [13], propose a proportional fair scheduling method based on greedy algorithm for uplink single carrier FDMA and utility-based schemes to improve sum rate capacity of the system. In [14] an enhanced two-step greedy resource allocation algorithm that achieves higher spectral efficiency than conventional greedy algorithms is proposed. Another enhanced greedy dynamic subcarrier allocation for SC-FDMA that performs better than Hungarian algorithm and traditional greedy algorithms is outlined in [15].

Analytical models based on Mixed Integer Programming (MIP) have been applied for resource allocation in LTE-A networks. In [16], the authors study uplink resource allocation algorithms for SC-FDMA systems. They develop BIP models for rate constraint among users with minimum number of subchannels. A joint resource allocation and adaptive modulation for SC-FDMA is proposed in [17]. In this work the problem is formulated as a BIP and converted into a continuous space canonical dual problem which resembles concave maximization problem. In [18], an iterative power efficient scheduler that solves BIP problem for uplink LTE is proposed. In [8], a QoS aware power efficient scheduler for the LTE uplink is introduced with the authors exploring power efficient scheduling for mixed streaming services in uplink LTE systems aimed at minimizing total transmission power for users. The optimization problem is formulated as a BIP problem, and then solved using low complexity greedy algorithm. Studies on power allocation in SC-FDMA have been performed in [19], [20]. In [19] a joint RB and power allocation is developed to maximize sum throughput while adhering to all SC-FDMA constraints and QoS requirements of M2M devices. The optimization problem is solved using Lagrange duality method. A study of uplink scheduling and power allocation with M2M/H2H in LTE-A networks is performed in [20]. A sum-throughput optimization resource allocation problem is formulated and solved using Lagrange dual decomposition algorithm. In [21] a mixed integer nonlinear programming (MINLP) power and channel allocation problem aimed at maximizing the sum throughput of active cell users and feasible device to device multicast groups is presented. The authors in [22] explore uplink resource allocation in LTE-A networks with the aim of maximizing total throughput of the cell given exclusivity, adjacency and power constraints pertaining to SC-FDMA. In their work they describe heuristic algorithms for allocating physical resource blocks and power in LTE-A uplink.

Research efforts considering energy efficiency in SC-FDMA have been done in [23], [24], [25], [26]. In [23], a joint user pairing and resource allocation with QoS restrictions for SC-FDMA is investigated. A multi-user energy efficient scheduler for SC-FDMA with queue state information (QSI) and QoS constraints is designed. An investigation of maximizing energy efficiency in

SC-FDMA is done in [24]. To address the energy efficiency the authors compare the optimal energy efficient resource allocation and heuristic sub-optimal energy efficient resource allocation algorithms. A design of a QoS based energy efficient SC-FDMA is explored in [25]. After formulating the optimization problem with the aim of maximizing the overall capacity through power and RB allocation, it is solved using canonical duality theory. A study of energy efficient resource and power allocation for underlay multicast Device-to-Device (D2D) transmission is undertaken in [26]. An optimization model with the aim of maximizing energy efficiency of D2D is constructed, and a heuristic model for channel and power allocation is applied.

To our knowledge the works that involve biological resource allocation in SC-FMDA are done in (27 to 30). A genetic algorithm in resource scheduling in LTE uplink is presented in [27]. Potential solutions to the non-convex optimization problem that arises due to SC-FDMA constraints are generated as chromosomes and a fitness function is then used to evaluate all chromosomes and desirable ones selected. An RB allocation scheme based on genetic algorithm and coordination over the $X2$ interface for non-mobile users is presented in [28]. The aim of the work is to optimize RB assignment using GA and maximizing channel capacity by exploiting information exchange over the $X2$ interface. A study of resource allocation for uplink LTE in mixed traffic environments based on GA is carried out in [29]. A three step GA based scheduling algorithm with a demonstration of how to code chromosomes with feasible scheduling solutions is outlined and the performance the algorithm evaluated on throughput and packet delay metrics. In [30] the authors examine how to optimize RB allocation in cloud radio access network for LTE, based on genetic algorithm. There is limited work on the application of combinations of biological schemes for resource allocation in uplink LTE-A, though applied in other scenarios. In [31], an ant colony particle swarm optimization algorithm is developed to optimize data clustering processes. The design of truss structures using particle ant swarm optimization is developed in [32]. In [33], PSO is employed to optimize an ant colony system parameters in specified Travelling Salesman Problems. Additional applications of particle swarm optimization are outlined in [34], [35].

The popularity of application of conventional RA methods such as game theory, greedy algorithm, analytical and GA remains undoubted. The same cannot be said of metaheuristic algorithms such as PSO, ACO and their hybrids, especially for RA on LTE uplink. Motivated by this perspective, this work makes the following contributions: it formulates the RA problem for uplink LTE-A network with exclusivity and contiguity constraints, investigates the application of metaheuristic algorithms (ACO and PSO) resource scheduling in SC-FDMA and proposes an Adaptive Particle Ant Swarm Optimization (APASO) resource scheduling for SC-FDMA, and finally, compares the performance of the proposed algorithms to that of the analytical Lagrangian based optimization. The developed results indicate near-optimal performance of metaheuristic algorithms when compared to analytical Lagrangian-based optimization with APASO outperforming PSO and ACO.

4 System Model

In this work, the uplink of a heterogeneous multi-user LTE-A network using SC-FDMA is considered. Assume a two-tier macrocell environment populated with base stations and user equipments (UEs). A macro base station (MBS), which serves as the eNodeB, is located at the center and serves M MUEs. The macrocell is overlaid with F femto base stations (FBS) with each FBS serving K FUEs. FUEs and MUEs share a set of $N = \{1, ..., N\}$ orthogonal Resource Block(RB)s. Each RB consists of 12 subcarriers as stipulated by the LTE-A specification [1]. The eNodeB manages the transmission of the K FUEs randomly distributed in the environment. After evaluating the channel conditions for each Transmission Time Interval (TTI), the resource scheduling algorithm in the eNodeB allocates RBs according to each UE's channel Signal-to-Interference-plus-Noise power Ratio (SINR). The channel is modelled as a block Rayleigh fading channel.

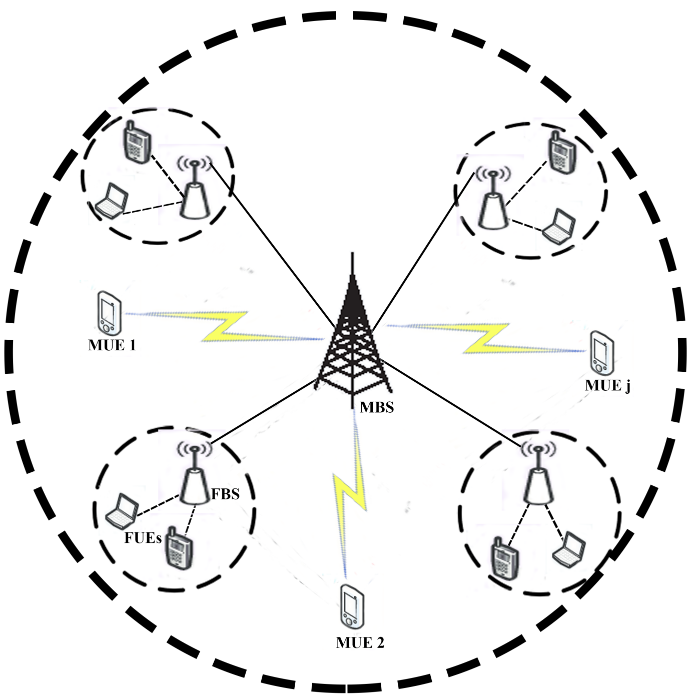

Fig. A.1: Heterogeneous macrocell-femtocell network architecture

Considering the heterogeneous network of Fig.A.1, the received signal at the i^{th} FBS from the

$k^{th} FUE$ on the n^{th} RB, $y_{k,n}^{FBS,i}$, is given by

$$y_{k,n}^{FBS,i}(t) = \underbrace{h_{k,n}^{FUE,i}(t)\sqrt{P_{k,n}^{FUE,i}}x_{k,n}^{FUE,i}}_{\text{Desired signal}} + \underbrace{\sum_{l \neq k}^{K} h_{l,n}^{FUE,i}(t)\sqrt{P_{l,n}^{FUE,i}}x_{l,n}^{FUE,i}}_{I_{k,n}} + \underbrace{\sum_{m=1}^{M} h_{m,n}^{MUE}(t)\sqrt{P_{m,n}^{MUE}}x_{m,n}^{MUE,i}}_{I_{CT}}, \tag{A.1}$$

where $x_{k,n}^{FUE,i}$ and, $x_{l,n}^{FUE,i}$ are message symbols from k^{th} and l^{th} FUEs on n^{th} RB at the i^{th} FBS, $x_{m,n}^{MUE,i}$ are message symbols from m^{th} MUE on n^{th} RB at the i^{th} FBS, $h_{k,n}^{FUE,i}$ is the channel gain of k^{th} FUE on n^{th} RB connected to the i^{th} FBS, $h_{l,n}^{FUE,i}$ are channel gains from other FUEs utilizing the same RB connected to the same FBS, $h_{m,n}^{MUE}$ is the channel gain of m^{th} MUE on n^{th} RB in the vicinity of the i^{th} FBS, $P_{k,n}^{FUE,i}$ is the transmit power of the k^{th} FUE on the n^{th} RB served by the i^{th} FBS, $P_{l,n}^{FUE,i}$ is the transmit power of other FUEs utilizing the n^{th} RB connected to the same FBS, $P_{m,n}^{MUE}$ is the transmit power of the m^{th} MUE transmitting on the n^{th} RB close to the FBS. $I_{k,n}$ is the interference from other FUEs' transmissions connected to the same FBS in the network to FUE k, and I_{CT} is cross-tier interference between transmissions of the MUEs and the FUEs.

The SINR, $\Gamma_{k,n}^{FUE,i}$, of k^{th} FUE on the n^{th} RB connected to the i^{th} FBS is given by

$$\Gamma_{k,n}^{FBS,i} = \frac{|h_{k,n}^{FUE,i}(t)|^2 P_{k,n}^{FUE,i}(t)}{\sum_{l \neq k}^{K} |h_{l,n}^{FUE,i}|^2 P_{l,n}^{FUE,i} + I_n^M + \sigma^2}, \tag{A.2}$$

where $I_n^M = \sum_{m=1}^{M} |h_{m,n}^{MUE,i}(t)| P_{m,n}^{MUE}$, σ^2 is additive white Gaussian Noise(AWGN). The data rate , $R_{k,n}^{FUE,i}$, of k^{th} FUE connected to i^{th} FBS using RB n is given by

$$R_{k,n}^{FUE,i}(t) = Blog_2(1 + \Gamma_{k,n}^{FBS,i}), \tag{A.3}$$

where B is the bandwidth of each RB in a small cell. It is assumed that all N RBs are reused at each Femto Base Station (FBS). Let $\mu_{i,k,n}$ be a binary variable that represents the allocation of n^{th} RB to k^{th} UE in i^{th} FBS, defined as

$$\mu_{i,k,n} = \begin{cases} 0, if \quad UE_k \quad is \quad not \quad assigned \quad RB, \\ 1, if \quad UE_k \quad is \quad assigned \quad RB. \end{cases} \tag{A.4}$$

The average throughput of small cells can be expressed as

$$C^{FBS} = \sum_{i=1}^{F} \sum_{k=1}^{K} \sum_{n=1}^{N} \mu_{i,k,n} R_{k,n}^{FUE,i}. \tag{A.5}$$

The total power consumed in all small cells is

$$P_T^{FBS} = \sum_{i=1}^{F} \sum_{k=1}^{K} \sum_{n=1}^{N} \mu_{i,k,n} P_{k,n}^{FUE,i} + P_{i,C}, \tag{A.6}$$

where $P_{i,C}$ is the power consumed by each femto base station to service FUEs connected to it. Energy efficiency (EE) for each femto cell is defined as

$$\eta_e(R,P) = \frac{C^{FBS}}{P_T^{FBS}}. \tag{A.7}$$

The optimization problem relating to energy efficiency of the entire network can then be formulated as

$$\max_{\mu_{i,k,n}, P_{k,n}^{FUE,i} \geq 0} \{\eta_e(R,P)\}, \tag{A.8}$$

subject to :

$$C1 : \sum_{n=1}^{N} \mu_{i,k,n} R_{k,n}^{FUE,i} \geq R_{min}^{FUE},$$
$$C2 : \sum_{n=1}^{N} \mu_{i,k,n} P_{k,n}^{FUE,i} \leq P_{max},$$
$$C3 : P_{k,n}^{FUE,i} \geq 0,$$
$$C4 : \sum_{k=1}^{K} \sum_{n=1}^{N} \mu_{i,k,n} P_{k,n}^{FUE,i} \leq I_{CT} \forall n,$$
$$C5 : \mu_{i,k,n} \in 0, 1,$$
$$C6 : \sum_{n=1}^{N} \mu_{i,k,n} \leq 1,$$

where $C1$ sets the minimum QoS requirement for k^{th} FUE using n^{th} RB on the i^{th} FBS, $C2$ restricts the trasmit power of FUEs served by the i^{th} FBS, $C3$ ensures that the transmit power of FUEs is non-negative, $C4$ enforces the maximum tolerable cross-tier interference, I_{CT}, is not exceeded. $C5$ and $C6$ are exclusivity constraints that ensure that an RB allocation pattern is only used by one FUE in each FBS.

5 Resource block scheduling

The objective of most resource scheduling algorithms is to utilize the available channel information to allocate resources and ensure that data is transmitted on RBs with good channel gains. After formulating the resource allocation problem in SC-FDMA using Binary Integer Problem (BIP), the optimal solution can be derived using analytic methods such as Lagrangian optimization, meta-heuristic algorithms such as PSO, ACO or the developed APASO.

A binary user pattern allocation matrix, $A_{RB,n}^{PT,P}$ consisting of row vectors $RB_n = \{RB_1, RB_2, ..., RB_N\}$ resource blocks and column vectors $PT_p = \{PT_1, PT_2, ..PT_P\}$

possible RB allocation patterns is constructed. It is noted in [8] that the number of allocation patterns, P, for N RBs is given by

$$P = \left[\frac{1}{2}(N(N+1))\right]. \tag{A.9}$$

Considering a scenario with 4 RBs the allocation patterns are $P = 11$ (including no allocation). The RB pattern allocation matrix adhering to the adjacency and contiguity constraint is given by

$$A_{RB,n}^{PT,p} = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 & 0 & 1 & 1 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 1 & 0 & 0 & 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 1 & 1 \end{bmatrix}. \tag{A.10}$$

The matrix can be explained as follows; the first column represents pattern 1, PT_1, where no RBs are allocated to any user, the second column, PT_2, where RB_1 is allocated to a user, whereas 7th column, PT_7 where RB_2 and RB_3 are allocated to a single user, etc. Note that matrix has the contiguity and exclusivity constraints embedded in it. The column order can change but the patterns remain the same. To illustrate how this allocation matrix is used to assign RBs to user equipment k , let

$$\mu_k^n = \begin{cases} 1, if \quad UE \quad k \quad is \quad assigned \quad RB \quad n \\ 0, Otherwise. \end{cases} \tag{A.11}$$

Note that $\mu_k^n \subseteq \mu_{i,k,n}$ of equation (A.4). For a case where one user UE_1 is allocated one RB and the second user UE_2 is allocated two RBs, the possible allocation will be given by the matrix,$A_{UE,k}^{PT,n}$, of dimension $K \times N$, where K is the maximum number of users given by

$$A_{UE,k}^{PT,p} = \mu_k^n A_{RB,n}^{PT,p} = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix}, \tag{A.12}$$

where UE_1 is allocated PT_3 hence utilizes RB_2 and UE_2 is allocated PT_8 and hence utilizes RB_3 and RB_4 (see equation A.10). Note that no user can be allocated two patterns and two users cannot share the same RB at the same time i.e. some patterns cannot be used at the same time e.g. PT_4 and PT_8 as there would be no exclusivity in RB_3. These limitations are the ones that make resource allocation on LTE-E uplink complicated. The RB and user pattern allocation matrix $A_{RB,n}^{UE,k}$ can be of the form

$$A_{RB,n}^{UE,k} = \begin{bmatrix} 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ 0 & 0 & \dots & 1 \\ 0 & 0 & \dots & 1 \end{bmatrix}, \tag{A.13}$$

where UE_1 is allocated PT_2 hence utilizes RB_1, UE_2 is allocated PT_3 hence utilizes RB_2 and UE_K is allocated PT_8 and hence utilizes RB_3 and RB_4. Noting that only one user can be allocated an RB, it collapses into a **RB scheduling vector** , $V_{sc}[RB_n]$ given by

$$V_{sc}[RB_n] = [UE_1 UE_2 \dots UE_K], \tag{A.14}$$

where UE_i is allocated RB_n (the index of the scheduling vector). Different combinations of the allowed scheduling vector results in different performance parameters. The determination of the right combination is important in the system optimization and thus different optimization algorithms are required to determine the optimal allocation. These are presented below.

5.1 Lagrangian Optimization

The optimization problem in equation (A.8) is non-convex. To apply Lagrangian optimization solution, equation (A.8) needs to be converted from its non-convex nature into a convex problem. Following nonlinear fractional programming Dinkelbach approach in [36], the transformed optimization problem in equation (A.8) is written as

$$\max_{\mu_{n,k},p\geq 0} \underbrace{\sum_{i=1}^{F}\sum_{k=1}^{K}\sum_{n=1}^{N}\mu_{i,k,n}R_{i,k,n}^{FUE}}_{C^{FBS*}} - \eta_e \underbrace{(\sum_{i=1}^{F}\sum_{k=1}^{K}\sum_{n=1}^{N}\mu_{i,k,n}P_{k,n}^{FUE,i} + P_{i,C})}_{P_T^{FBS*}}. \tag{A.15}$$

This subtractive form of the objective function will be optimized when $C^{FBS*} - \eta_e P_T^{FBS*} = 0$. It can be noted that equation (A.15) is monotonically decreasing with respect to η_e and an iterative approach can be employed to derive η_e^* which is the optimal energy efficiency. The Lagrangian function to the transformed objective function in equation (A.15) can then be formulated as

$$L(R,P,\eta_e,\Theta) = C^{FBS*} - \eta_e P_T^{FBS*} + \gamma(\sum_{n=1}^{N}\mu_{i,k,n}R_{k,n} - R_{min}^{FUE,i}) + \lambda(P_{max} - \sum_{n=1}^{N}\mu_{i,k,n}P_{k,n}^{FUE,i}) + \rho(I_{CT} - \sum_{k=1}^{K}\sum_{n=1}^{N}\mu_{i,k,n}P_{k,n}^{FUE,i}) + \sum_{i=1}^{F}\sum_{k=1}^{K}\delta(1 - \sum_{n=1}^{N}\mu_{i,k,n}), \tag{A.16}$$

where $\Theta = (\gamma \geq 0, \lambda \geq 0\rho \geq 0, \delta \geq 0)$ are duality variables for constraints C1, C2, C4 and C6. The constraints C3 and C5 are absorbed by KKT conditions. The dual problem, $\Omega(\eta_e\gamma, \lambda, \rho, \delta)$, and its constraints can be expressed as [17]

$$\Omega(\eta_e, \gamma, \lambda, \rho, \delta) = \min_{\gamma,\lambda,\rho,\delta} L(\gamma, \lambda, \rho, \delta) = \min_{\gamma,\lambda,\rho,\delta} \max_{R,P} L(\eta_e, \gamma, \lambda, \rho, \delta), \tag{A.17}$$

subject to

$$\sum_{n=1}^{N}\sum_{k=1}^{K} \mu_{n,k} A_{RB,k}^{PT,n} = 1,$$

$$\mu_{k,n} \in 0, 1,$$

$$\sum_{n=1}^{N} \mu_{k,n} = 1,$$

$$0 \leq P_{k,n}^{FUE,i} \leq P_{max}.$$

In solving, decompose $\Omega(\gamma, \lambda, \rho)$ into $L = F \times N$ subproblems to be independently solved for each RB allocation. For instance, the l^{th} subproblem can be represented as

$$\max_{U_l,P_l,I_l} L_l(U_l, P_l, I_l, \Theta), \tag{A.18}$$

where U_l is the vector $U_l = [\mu_1, \mu_2, \ldots, \mu_K]$ which is all zeros except at the allocated RB pattern, P_l is the power allocation matrix at l^{th} allocation pattern, and I_l is the cross tier interference in l^{th} subproblem. Note that equation (A.18) is subject to the same constraints of equation (A.17). The Lagrangian in equation (A.16) can be rewritten as

$$L(\{P\}, \{U\}, \eta_e, \Theta) = \sum_{i=1}^{F}\sum_{n=1}^{N} L_{i,n}(\{P\}, \{U\}, \Theta) + \sum_{n=1}^{N} \rho I_{CT} - \sum_{i=1}^{F}\sum_{k=1}^{K} R_{min}^{FUE,i} + \sum_{i=1}^{F}\sum_{k=1}^{K} \delta_{k,n}, \tag{A.19}$$

where

$$L_{i,n}(\{P\}, \{U\}, \Theta) \;=\; \sum_{k=1}^{K} \mu_{i,k,n} R_{k,n}^{FUE,i} \;+\; \sum_{k=1}^{K} \eta_e P_{k,n}^{FUE,i} \;-\; \lambda P_{k,n}^{FUE,i} \;-\; \sum_{k=1}^{K} \delta_{k,n}. \tag{A.20}$$

The optimal value for subproblems is then solved using KKTs to obtain

$$P_{k,n}^{FUE,i} = \frac{P_{k,n}^{FUE,i*}}{\mu_{i,k,n}} = min\left\{\left(\frac{(1+\gamma_{i,k,n})B}{(1+\gamma_{i,k,n})(\Gamma_{k,n}^{FBS,i})B + ln2(\eta_e + \lambda + I_n^M)}\right)^{+}, Pmax\right\}, \tag{A.21}$$

where $I_n^M = \rho h_{m,n}^{MUE,i}$ The partial derivative of the Lagrangian with respect to $\mu_{i,k,n}$ from equation (A.20) is

$$\frac{\partial L_{i,n}}{\partial \mu_{i,k,n}} = S_{i,k,n} - \delta_{k,n}, \tag{A.22}$$

where

$$S_{i,k,n} = (1+\gamma_{k,f})Blog_2\left(1+\frac{P_{k,n}^{FUE,i}|h_{k,n}^{FUE,i}|^2}{I_{k,n}+I_{CT}+\sigma^2}\right) - (1+\gamma_{k,f})\frac{B}{N}\left(1+\frac{P_{k,n}^{FUE,i}|h_{k,n}^{FUE,i}|^2}{I_{k,n}+I_{CT}+\sigma^2}\right) - \lambda P_{k,n}^{FUE,i} - \rho P_{k,n}^{FUE,i} h_{k,n}^{MUE,i}. \tag{A.23}$$

$$\mu_{i,k,n} = 1 \Big| k^* = maxS_{i,k,n}. \tag{A.24}$$

Having solved all the subproblems of equation (A.18), a subgradient method is employed to update dual vectors (γ, λ, ρ) as follows

$$\gamma^{t+1} = \gamma^t - \alpha_1 \left[\sum_{n=1}^{N} \mu_{n,k} R_{k,n}^{FUE,i} - R_{min}^{FUE}\right], \tag{A.25}$$

$$\lambda^{t+1} = \lambda^t - \alpha_2 \left[P_{max} - \sum_{n=1}^{N} \mu_{n,k} P_{k,n}^{FUE,i}\right]. \tag{A.26}$$

$$\rho^{t+1} = \rho^t - \alpha_3 \left[I_{CT} - \sum_{k=1}^{K}\sum_{n=1}^{N} \mu_{n,k} P_{k,n}^{FUE,i}\right], \forall n \tag{A.27}$$

where α_1,α_2, and α_3 are step sizes. The Lagrangian optimization process is implemented as indicated in Algorithm 1.

5.2 Particle Swarm Optimization(PSO)

5.2.1 Principle of Operation

In the basic PSO [7], each particle represents a potential solution to the objective function $F(x)$ where x is the decision vector in D dimensional search space. An i^{th} particle has a position in the search space represented by position vector $x_i = [x_{i1}, x_{i2}, \ldots, x_{iD}]$ and it moves about in the search space with velocity $v_i = [v_{i1}, v_{i2}, \ldots, v_{iD}]$. As particles travel in the search space they evalute the fitness function (f) related to $F(x)$ and store the position of their highest personal fitness, f_{pbest}, and that of the entire swarm, f_{gbest}. Given a swarm of P_n particles, the personal best, $P_{i,f_{pbest}}$, and global best values, $P_{i,f_{gbest}}$, of the particles can be expressed as

$$P_{i,f_{pbest}} = arg \quad min[f_{pbest}, x_{id}], \tag{A.28}$$

Algorithm 1: Iterative Resource Allocation Algorithm

Initialize I_n^{th}, λ,ν,μ ,$P_{k,n}^{FUE}$ (uniform power),$\eta_e\{th\}$
while *(convergence not reached)* **do**
    repeat for *i=1: F* **do**
        for *k =1:K* **do**
            for *n =1:N* **do**
                Determine $\mu_{i,k,n}$, equation (A.24),
                Calculate data rate, $R_{k,n}^{FUE,i}$, equation (A.5),
                Calculate $P_{k,n}^{FUE}$, equation (A.21),
                Compute η_e, equation (A.21),
            end
        end
    end
    Update dual variables (γ, λ, ρ) equation (A.25), (A.26), (A.27).
    until convergence to dual optimum.
end

$$P_{i,f_{gbest}} = arg \quad min[f_{gbest}, x_{id}], \tag{A.29}$$

At each instant particles update their velocity vector to attain their previous best fitness and migrate towards the swarm's global best fitness value. Each particles velocity, v_{id}^{t+1}, is computed according to

$$v_{id}^{t+1} = wv_{id}^t + c_1 r_1 (P_{i,f_{pbest}} - x_{id}^t) + c_2 r_2 (P_{i,f_{gbest}} - x_{id}^t), \tag{A.30}$$

where w is particles inertia, $P_{i,f_{pbest}}$ is the personal best position of the particle, c_1 and c_2 are personal and social learning rates respectively. The variables r_1 and r_2 are random values normally in the range 0 to 1. The particle's position is updated as

$$x_{id}^{t+1} = x_{id}^t + v_{id}^{t+1}, \tag{A.31}$$

where v_{id} is the velocity vector with an equivalent dimension D as the position vector. The dimension of the search space is problem specific.

5.2.2 PSO resource block scheduling

In application of PSO to LTE-A RA, particles represent feasible solutions to the resource scheduling optimization problem. The fitness function, $F(x)$, is the energy efficiency optimization problem of equation (A.8) expressed as

$$F(x) \Leftrightarrow max\{\eta_e(R, P)\}. \tag{A.32}$$

As particles "fly" over the search space to discover UE-RB assignments which yield good energy efficiency solutions, they evaluate the fitness function in equation (A.32). A particle in this instance is a $1 \times N$ vector representing the allocation of N RBs to the K UEs. In every Transmission Time Interval (TTI), the position of each particle, x_{id} represents a feasible RB assignment and is constructed to form the resource scheduling vector defined as a position vector $x_{id} = [x_{i1}, x_{i2}, \ldots, x_{iN}]$,

$$x_{id} \Leftrightarrow V_{sc}[RB_n], \tag{A.33}$$

where $V_{sc}[RB_n]$ is given by equation (A.14). Particles then update their personal best positions which correspond to the best scheduling solution the particle has discovered thus far. The global best particle position is updated if the personal best of the particle at that instant is found to be better than the current global best position. The implemented scheduling algorithm is outlined in Algorithm 2.

5.3 Ant Colony Optimization (ACO)

5.3.1 Principle of Operation

In ACO, a discrete combinatorial optimization problem is modelled using a construction graph. The optimization problem is modelled as a graph coloring problem represented by $G = (V, E)$ where V is the number of vertices and E is the number of edges. In the Ant Colony Optimization Assignment Type Problem (ACO ATP) [37], [38] i nodes are assigned j colors where items are represented as nodes on the graph and objects to be assigned as colors. Artificial ants create paths which represent feasible solutions as they travel through the graph. In each path, ants choose a path $P_{i,j}$ which represents an assignment of j objects to i items, and evaluate the fitness function $F_{i,j}(x)$ which is related to the objective function being optimized.

$$P_{i,j} = max\{F_{i,j}(x)\}. \tag{A.34}$$

They choose the optimal path, $P^{op}_{i,j}$, that maximizes the fitness function F^{op}_{ij},

$$P^{op}_{i,j} = max\{F^{op}_{i,j}(x)\}. \tag{A.35}$$

Algorithm 2: PSO SC-FDMA Resource Scheduling

Input:
UEs: U = { 1,...,k,...,UE_K }
RBs: R = {1,...,n,... RB_N }
Initialize: c_1, c_2, r_1, r_2, w
while *(convergence not reached)* **do**
    for *i=1:F* **do**
        for *n =1:N* **do**
            Generate random positions of particles, equation (A.31).
            Perform RA, equation (A.14) ,
            Update available resources, equation A.8 $(C5\&C6)$,
            Determine the throughput equation (A.5),
            Determine power, equation (A.6),
            Evaluate particle fitness, equation (A.32),
            Update,f_{pbest}, equation (A.28),
            if $P_{i,f_{gbest}}$ > $P_{i,f_{gbest}}$ **then**
                Update, $P_{i,f_{gbest}}$, equation (A.29),
            end
            Implement power allocation in RBs while ensuring it is below the total power P_T,
            Continue process until convergence reached or number of iterations exceeded.
        end
    end
end

An ATP ACO set up usually requires two probabilistic rules for choosing nodes and colors. The first probability, $p^{'}_{i,j}(t)$, for ant a choosing the next node when it is at node i, is given by

$$p^{'}_{i,j}(t) = \frac{\tau^{'\alpha}_{i,j}(t)\eta^{'\beta}_{i,j}(t)}{\sum_{j \in S^k_i(t)} \tau^{'\alpha}_{i,j}(t)\eta^{'\beta}_{i,j}(t)}, \tag{A.36}$$

where,α, β are weighting factors for pheromone, $\tau^{'}_{i,j}$, and desirability, $\eta^{'}_{i,j}$, and $S^k_i(t)$ is set of feasible nodes from ant a at node i. The desirability of ant a choosing the next node is given by the heuristic function, $\eta^{'}_{i,j}(t)$,

$$\eta^{'}_{i,j}(t) = \frac{1 + |N^k_{unassigned}|}{1 + |N_{nei,i}|}, \tag{A.37}$$

where $|N^k_{unassigned}|$ is the number of neighbours to the current node that have not been allocated objects, and $|N_{nei,i}|$ is the number of neighbors from the perspective of the ant when at node i. The pheromone in previously chosen nodes is defined as

$$\tau^{'}_{i,j}(t) = \frac{F^{best}_{i,j}}{|N^{best}_i(t)|}, \tag{A.38}$$

where $F^{best}_{i,j}$ is the fitness function of best ant, and N^{best}_i is the set of feasible nodes from the perspective of best ant at node i. The second probability, $p^{''}_{i,o}(t)$, of choosing an object to assign for the current node from the set of objects, N_o is given by

$$p^{''}_{i,o}(t) = \frac{\tau^{''\alpha}_{i,c}(t)\eta^{''\beta}_{i,o}(t)}{\sum_{j \in N_o} \tau^{''\alpha}_{i,c}(t)\eta^{''\beta}_{i,o}(t)}, \tag{A.39}$$

where the heuristic function, $\eta^{''}_{i,o}$, is defined as

$$\eta^{''}_{i,o}(t) = \frac{1 + n_{previous-best}}{1 + n_{available-obj}}, \tag{A.40}$$

where $n_{previous-best}$ is the number of elements in the set of previously assigned objects, $n_{available-obj}$ is the number of objects available for allocation. The pheromone, $\tau^{''}_{i,c}$, is updated using

$$\tau^{''}_{i,c}(t) = \frac{n_{previous-best}}{|N^{Best}_i(t)|}. \tag{A.41}$$

The fitness function $F_{i,j}$ of each path which represents a solution to the optimization problem is calculated along each path and paths with higher fitness have more pheromones deposited on them.

5.3.2 Ant Colony Optimization(ACO) RA scheduling

On application to LTE-A RA UEs are represented by nodes and RB allocation patterns are associated with colors. A graph coloring property that no two adjacent nodes (UEs) have same colors is observed while also respecting the SC-FDMA requirement that if a UE is to be allocated more than one RB, such RBs should be contiguous. A path that represents the assignment of n RBs to k UEs can be formulated from equation (A.14) as

$$P_{k,n} \Leftrightarrow V_{sc}[RB_n]. \tag{A.42}$$

The optimal path, $P^{op}_{k,n}$, that maximizes optimization function is

$$P^{op}_{k,n} \Leftrightarrow \widetilde{V_{sc}}[RB_n] \Leftrightarrow max\{F_{k,n}(x)\}. \tag{A.43}$$

The fitness function, $F_{k,n}(x)$ is given by

$$F_{k,n} = max\{\eta_e(R,P)\}. \tag{A.44}$$

As ants traverse the search space they leave pheromone in paths that have higher fitness, i.e. RB allocations that have desirable energy efficient transmission rates in their path for other ants to follow in future travels. A colony of scheduling decisions is build by ants based on tours in which they discovered optimal sum rates. The applied ACO SC-FDMA Resource Scheduling algorithm is summarized in algorithm 3.

5.4 Adaptive Particle Ant Swarm Optimization (APASO)

5.4.1 Principle of Operation

Artificial *ant particles* possessing both attributes of PSO and ACO are created and randomly initialized in the search space. For all ant particles the fitness function, $F(x)$, is computed. To improve the performance of PSO a pheromone-guided mechanism is employed to indicate ant particles with more fitness. In [39], it is outlined how the inertia weight provides a balance between exploration and exploitation. Having a higher inertia weight in the beginning enables global search, while a lower inertia weight in later stages of algorithm execution improves convergence towards personal and global best values. In our proposed APASO we consider the modification of ant particles inertia weight as

$$w \Leftrightarrow \tau_{inter}, \tag{A.45}$$

where τ_{inter} is the inter ant particle pheromone given by

$$\tau_{inter} = \zeta\left(\left| \frac{min(F^t_{pbest}(x), \overline{F}_t(x))}{max(F^t_{pbest}(x), \overline{F}_t(x))} \right| \right), \tag{A.46}$$

Algorithm 3: ACO SC-FDMA Resource Scheduling

Input: UEs: U = { 1,...,k,...,UE_K}
RBs: R = {1,...,n,... RB_N }
Initialize: α , β , ρ
while *(convergence not reached)* **do**
    for *i=1:F* **do**
        for *k=1:K* **do**
            for *n =1:N* **do**
                Begin ant search for RBs in R that satisfy $(A.8, C1)$.
                Select UEs, equation (A.36)
                Assign RBs, equation (A.39).
                Update available resources, equation A.8 $(C5\&C6)$.
                Determine the throughput, equation (A.5)
                Calculate power consumption, equation (A.6)
                Evaluate fitness function, equation (A.44).;
                Update pheromone for higher fitness functions, equation (A.38) & (A.41).
                Implement power allocation in RBs while ensuring it is below the total power P_T;
                Continue process until convergence reached or number of iterations exceeded.;
            end
        end
    end
end

where ζ is a control parameter in the range [0,1], and $\overline{F}_t(x)$ is the mean fitness of all ant particles at t, and $F^t_{pbest}(x)$ is personal best fitness of ant particles at t. For a D-dimensional space, an ant particle has velocity, v^{t+1}_{id} and position, x^t_{id}, defined by

$$v^{t+1}_{id} = \tau_{inter} v^t_{id} + c_1 r_1 (p^t_{pb} - x^t_{id}) + c_2 r_2 (p^t_{gb} - x^t_{id}), \tag{A.47}$$

$$x^{t+1}_i = x^t_i + v^{t+1}_i, \tag{A.48}$$

where p^t_{pb} and p^t_{gb} are personal best and global best of ant particles defined similar to equations (A.28) and (A.29) respectively. In equation (A.45) applying the inter ant particle (τ_{inter}) pheromone to the first term on the right hand side of the equation enables diversity of ant particles' search in early iterations of the algorithm while increasing convergence in later iterations.

5.4.2 Adaptive Particle Ant Swarm Optimization (APASO) Scheduling

The proposed hybrid technique aims to exploit advantages of PSO and ACO to attain superior performance to the conventional algorithms. In the beginning stage of the scheduling process, PSO generates new random particle ants, and the ACO based pheromone mechanism generates pheromones for ant particles to mark solutions with higher fitness values. It is these favourable qualities of the PSO and ACO that have motivated the hybridization of PSO and ACO in the proposed APASO. The position of an ant particle is modelled as scheduling vector in a particular TTI as

$$x_{id} \Leftrightarrow V_{sc}[RB_n], \tag{A.49}$$

where $V_{sc}[RB_n]$ is defined as equation (A.14). The fitness function is formulated to solve the optimization problem in equation (A.8)

$$F(x) \Leftrightarrow max\{\eta_e(R, P)\}. \tag{A.50}$$

Each ant particle then stores its position together with its fitness value, and keeps updating velocity in equation (A.47) so that the ant particles maintain their migration towards better solutions. The mechanics of the APASO algorithm for RB scheduling in SC-FDMA is summarized in algorithm 4.

5.5 Computational Complexity of Algorithms

One of the challenges of metaheuristic algorithms is the difficulty in computing their time complexity as they do not guarantee finding global optimal solution. Following the work of [40], the time

Algorithm 4: APASO SC-FDMA Resource Scheduling

Input:

UEs: U = { 1,...,k,...,UE_K }

RBs: R = {1,...,n,... RB_N }

Initialize c_1, c_2, r_1, r_2, w,τ_{inter} **while** *(convergence not reached)* **do**

  for *i=1:F* **do**

    for *n =1:N* **do**

      Initialize random ant particles search, Allocate resources, equation (A.14), Determine the throughput, equation (A.5),

      Distribute pheromone τ_{inter}, equation (A.46),

      Evaluate fitness function for all ant particles, equation (A.50),

      Update the velocity and position vectors for ant particles, equations (A.47) & (A.48),

      Update pheromone, equation (A.46),

      Implement power allocation in RBs while ensuring it is below the total power P_T,

      Continue process until convergence is reached or number of iterations exceeded.

    end

  end

end

complexity of a metaheuristic algorithm depends on number of iterations, N_{ite}, and the number of ants, N_{ants} or particles, $N_{particles}$, and their running times. ACO time complexity, T_{ACO}, depends on the length of ant tours:

$$T_{ACO} = N_{ite} \times (N_{ants} \times (T_{tour} + T_{sel})), \tag{A.51}$$

T_{tour} is the running time it takes each ant hunting for food, and updating the pheromone on its track back to the nest, T_{sel} is the running time while assessing pheromones from previous travels and selecting those with better pheromones. Similarly, for the PSO the time complexity, T_{PSO}, can be estimated as

$$T_{PSO} = N_{ite} \times (N_{particles} \times (T_{pos} + T_{velUp})), \tag{A.52}$$

where T_{pos} is the running times for encoding and evaluating fitness of particles, and T_{velUp} is the time when the PSO is updating velocities of particles. In the case of the hybrid APASO algorithm the time complexity, T_{APASO}, can be written as

$$T_{APASO} = N_{ite} \times (N_{antparticles} \times (T_{pos} + T_{modVel})), \tag{A.53}$$

where $N_{antparticles}$ is the number of ant particles, T_{modVel} is the time for changing the velocity of ant particles to aggregate ant particles with previously higher fitness by applying pheromones as inertia weight.

6 Performance Evaluation

The simulation model is based on the uplink of 3GPP LTE-A network. A bandwidth of 5MHz with each RB having 180 kHz spacing (giving a total of 25 RBs per TTI) is assumed. As specified by the 3GPP each TTI is equivalent to 1ms and consists of 25RBs. In the network, the coverage radius of the macrocell is 500m and that of the femtocell is 10m. A minimal distance of 40m between FBSs is assumed, and a minimal distance of an MUE and an FBS is 15m. Where not specified, 5 MUEs uniformly distributed in the cell coverage area and 10 FUEs evenly distributed among FBSs are considered. A target BER of 10^{-3} is assumed. The channel model is represented by small scale Rayleigh fading, large scale path loss and log normal shadowing. Power spectral density of noise is -174dBm/Hz. It is assumed that base stations have perfect channel state information (CSI), and that the duration of CSI feedback and scheduling decisions between users and base stations is negligible. The rest of the simulation parameters are summarized in Table 1 and Table 2.

Fig. A.2 illustrates the effect of increasing power on sum throughput in the network. As the transmit power increases the SINR of FUEs increases which results in the sum- throughput of the system increasing. The analytic Lagrangian performs better than the metaheuristic algorithms with APASO

Table A.1: Simulation Parameters

System Parameters	Value
Bandwidth	5MHz
bandwidth per subchannel	180 kHz
Transmit time interval(TTI)	1 ms
Carrier Frequency	2.6 GHz
Noise power spectral density	-174 dBm/Hz
FBS static power,$P_{i,C}$	21 dBm
Radius of macrocell	500m
Radius of femtocell	10m
per subchannel peak power, $P_{k,n}^{peak}$	10 mW
per user max power,P_k^{max}	200mW
Shadowing	Lognormal,$\sigma = 8$ dB
Multipath Fading	Rayleigh

Table A.2: Simulation parameters for evolutionary algorithms

ACO	PSO	APASO
α =1.5	c1=c2 = 2	α =1, c1 =c2 = 1.5
β =2	w =1	β =1 , w=τ_{inter}
ρ =0.05	$wd = 0.99$	$\zeta = 0.4$
$ants = 10$	$particles = 10$	$particleants = 10$

outperforming the PSO and ACO. Note that the gradient of the graphs reduce to a saturation point due to excess power leading to increased interference in the network. As illustrated in Fig. A.3 the throughput capacity, from equation (A.5), of the system increases as the number of FUEs increases implying that an increasing number of UE-RB allocation results in increased RB utilization efficiency, and hence higher sum throughput of the system. This exemplifies multi-user diversity. Across all algorithms the gradient of the curves decreases due to decreasing number of RBs allocated to each FUE as FUE devices increase. The performance of all three algorithms is below that of the optimal analytic Lagrangian optimization algorithm with the APASO performing better than the PSO and ACO due to the inter ant particle pheromone in APASO helping to aggregate best performing ant particle. As expected, the optimal Lagrangian is observed to have better throughput performance [21], [41].

Fig. A.4 compares the transmit power vs average channel gain for the three algorithms with the

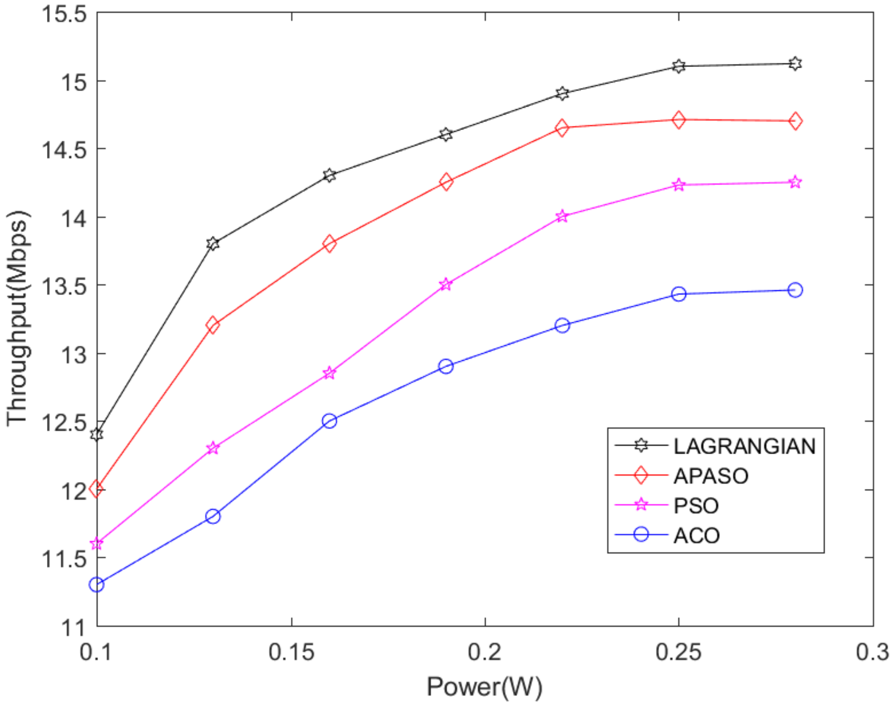

Fig. A.2: Throughput vs Transmit Power when N = 25 and K = 12, per subchannel peak power, $P_{k,n}^{peak}$ = 10mW, per user max power,P_k^{max} = 200mW. The power spectral density of noise is assumed to be -174dBm/Hz.

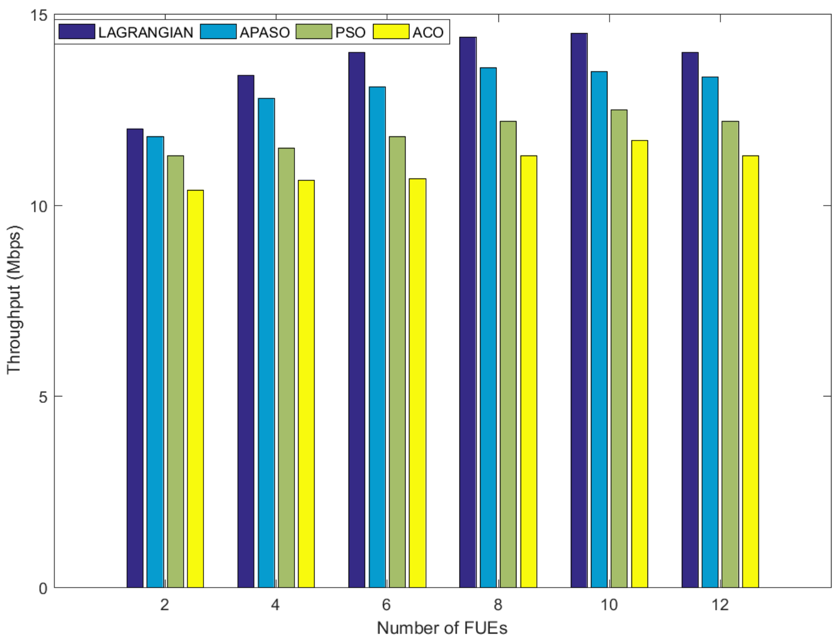

Fig. A.3: Throughput vs No of FUEs when the N = 25 and K = 12. Power spectral density of noise assume to be -174 dBm

analytic Lagrange dual algorithm being used as a benchmark. As channels with better SINR are discovered by optimization algorithms the transmit power of FUEs is reduced to meet the throughput

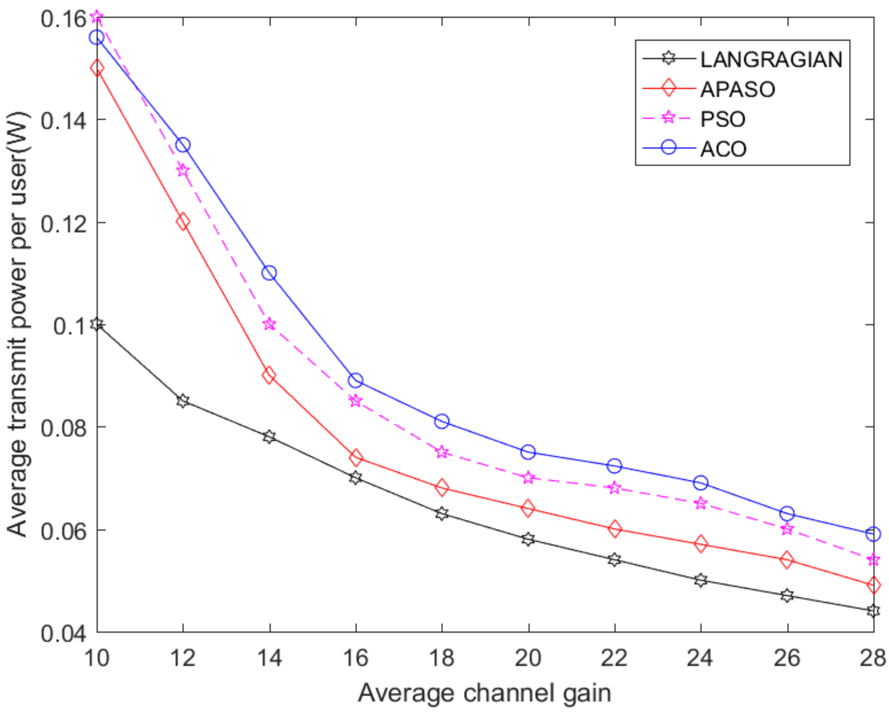

Fig. A.4: Average transmitted power per user per TTI, per subchannel peak power, $P_{k,n}^{peak}$ = 10mW, per user max power,P_k^{max} = 200mW. The power spectral density of noise is assumed to be -174dBm/Hz.

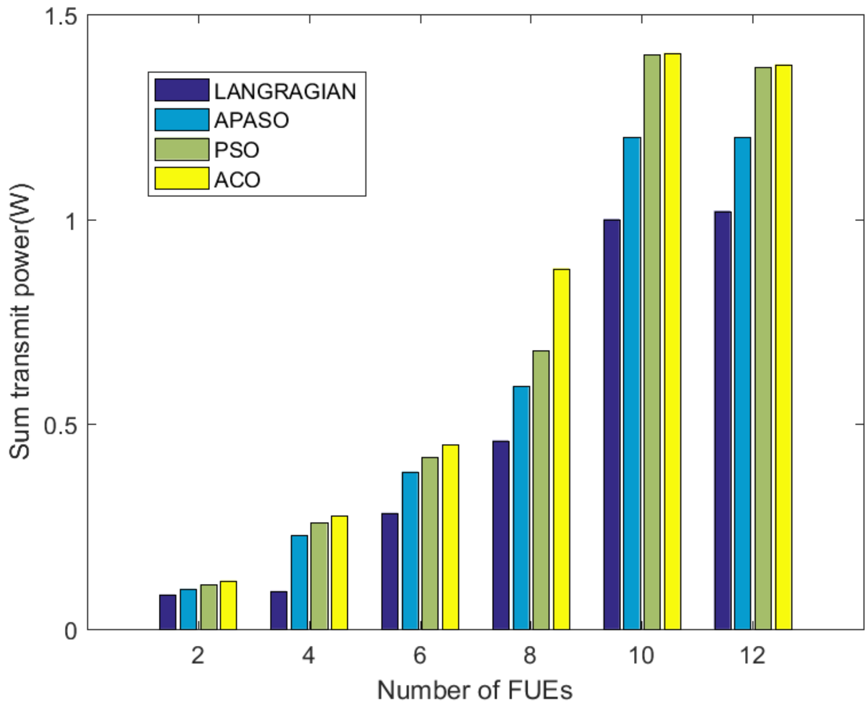

Fig. A.5: Sum-transmit power vs Number of FUEs, per subchannel peak power, $P_{k,n}^{peak}$ = 10mW, per user max power,P_k^{max} = 200mW. The power spectral density of noise is assumed to be -174dBm/Hz.

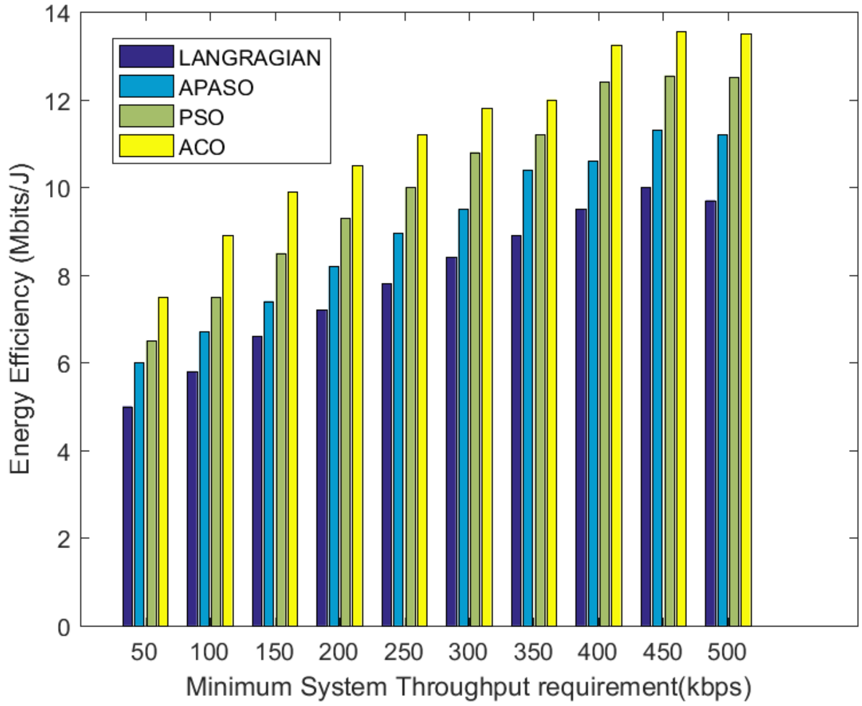

Fig. A.6: Energy efficiency vs Minimum system throughput for different minimum rate requirements, per subchannel peak power, $P_{k,n}^{peak}$ = 10mW, per user max power,P_{k}^{max} = 200mW.

requirements while minimizing FUE terminal power consumption. APASO has lower average transmit power as compared to PSO and ACO with the analytical Lagrangian having the lowest power consumption. The sum transmit power of FUEs versus the number of FUEs is shown in Fig. A.5. It can be observed that the APASO consumes less power than traditional PSO and ACO. This implies that the proposed APASO is able to search for RBs with better channel gains than other metaheuristic algorithms, and then adjust power allocated accordingly to meet minimum UE QoS requirements. This will help sustain UE battery life for longer periods. The optimal Lagrangian has lowest transmit power, a performance similar to that in [17] where it has lowest sum power as compared to the other proposed methods.

The energy efficiency versus minimum system throughput for each algorithm is illustrated in Fig. A.6 . The ACO has the lowest Energy Efficiency in terms of lower transmitted bits per joule, while the hybrid APASO outperforms the other meta-heuristic algorithms because of its ability to discover RBs with better SINR as compared to PSO and ACO resulting in enhanced throughput-to-power ratio in equation (A.7). Fig. A.7 shows that as the power is increased, the energy efficiency also increases. A higher transmit power leads to increased throughput and ultimately higher energy efficiency. There is a saturation point of the energy efficiency as power allocation has to be restricted below the interference threshold.

Fair distribution of resources among users is also one of the desirable metrics in resource allocation algorithms. A common approach to evaluating fairness is by employing Jains Fairness Index which is formulated as

$$J = \frac{\left(\sum_{k=1}^{K} R_{k,n}^{FUE,i}\right)^2}{K \times \sum_{k=1}^{K} (R_{k,n}^{FUE,i})^2}. \tag{A.54}$$

From Fig. A.8, the fairness index is lower in APASO, PSO than in ACO. In simulations, FUEs

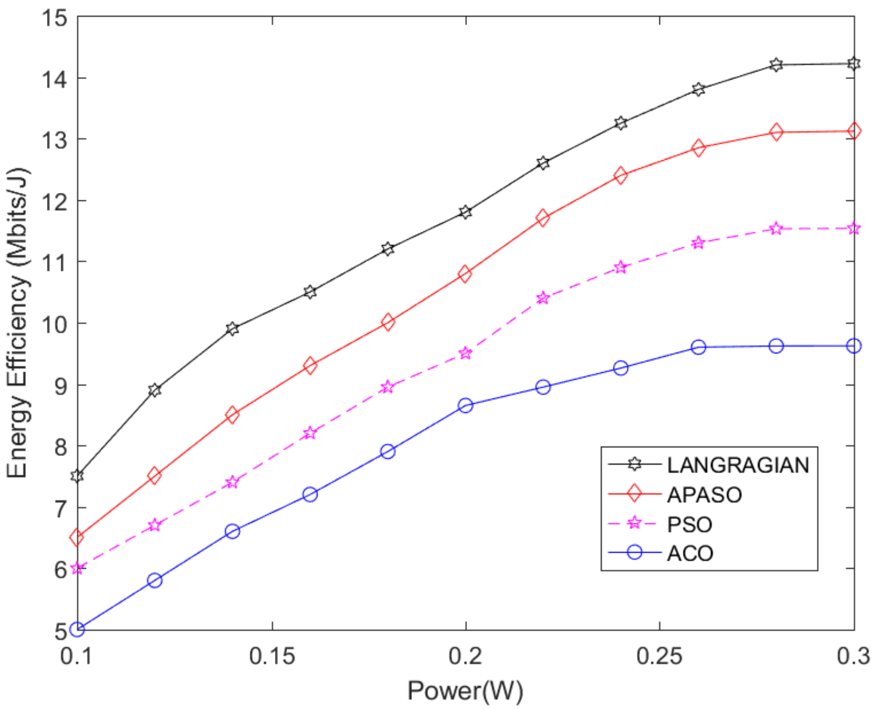

Fig. A.7: Energy Efficiency vs Power when N=25, K = 12, per subchannel peak power, $P_{k,n}^{peak}$ = 10mW, per user max power,P_k^{max} = 200mW.

with the best channel conditions are assigned more resources to optimize the sum throughput of the network while those with lower channel conditions are allocated less RBs. It can be observed that the hybrid algorithm exhibits less fairness than conventional PSO and ACO as it is more focused on maximizing throughput to power ratio, hence higher energy efficiency, by assigning better SINR RBs to FUEs with better channel conditions. The analytic Lagrangian method awards more RBs to users with higher metrics resulting in other users being starved of system resources. This low fairness is also observed in the Lagrangian application of [8].

In Fig. A.9 the running times of the algorithms have been measured using the MATLAB *tic-toc* function . It can be noted from Fig. A.9 that APASO has the lowest running time when compared to the PSO, ACO. The cooperation of the PSO and ACO enhances the performance in terms of reaching

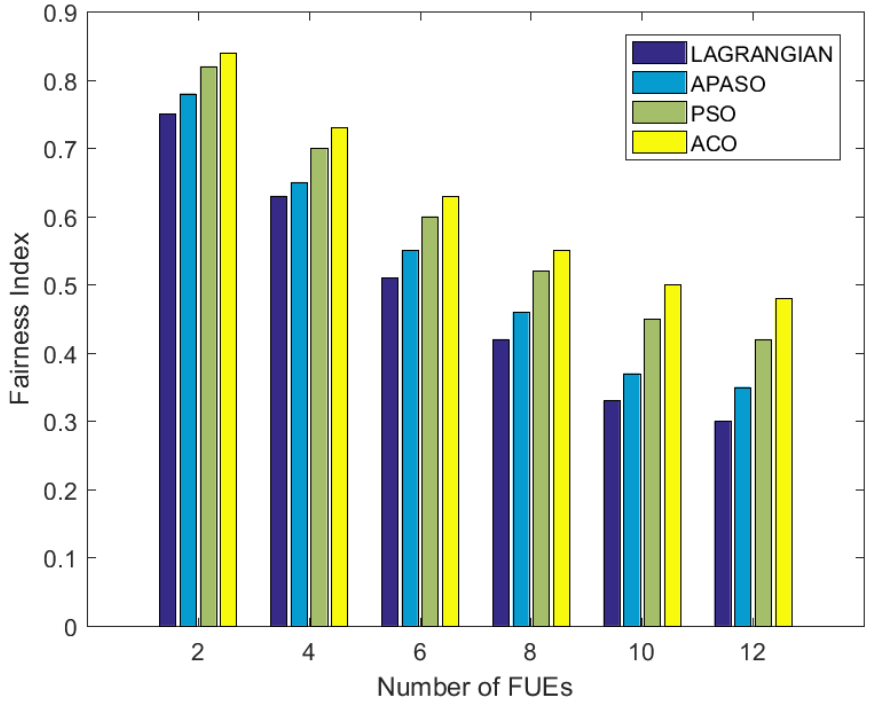

Fig. A.8: Comparison of Jain's Fairness index of algorithms

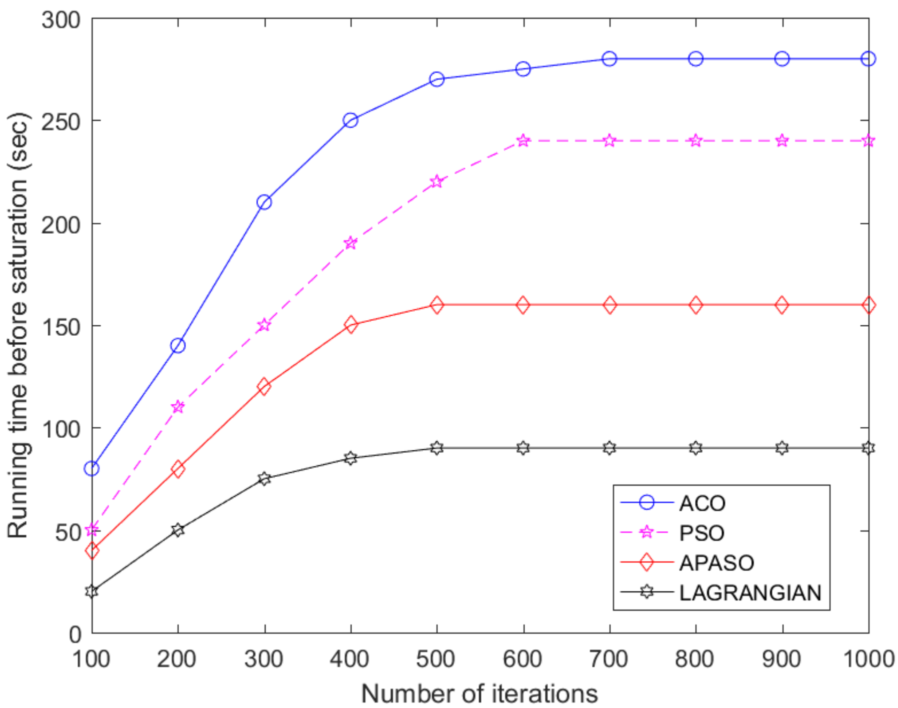

Fig. A.9: Running time (tic-toc) vs Number of iterations

near optimal solutions faster. This implies that computational time complexity in equation (A.53) is lower than that in equations (A.51) and (A.52).

The convergence of each algorithm was evaluated by plotting an average of 1000 TTIs for each algorithm as illustrated in Fig. A.10. The minimum system requirement is fixed at 200 kbps for this

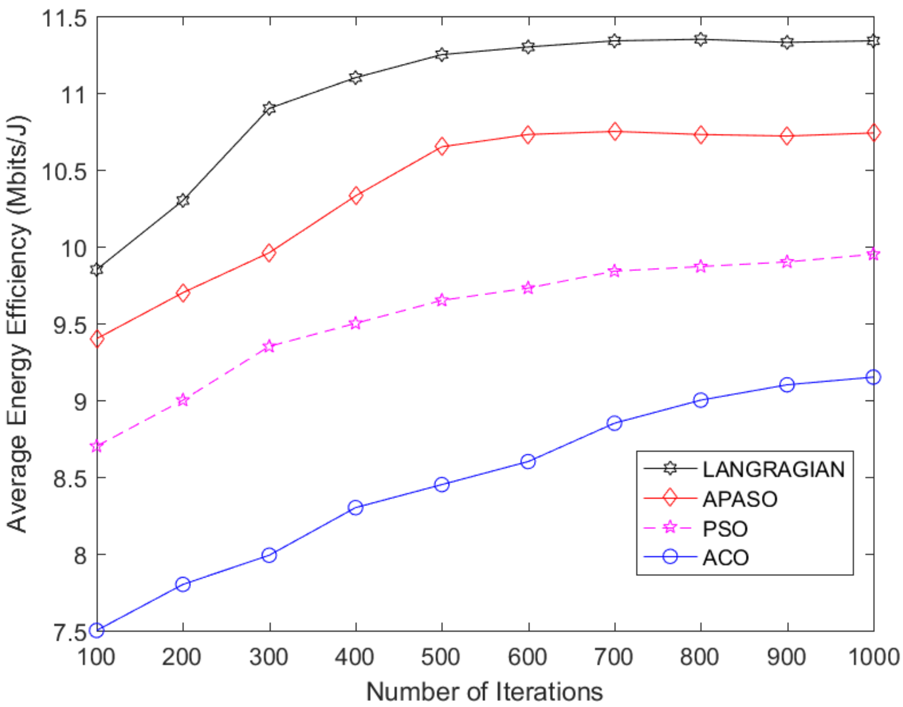

Fig. A.10: Average Energy Effiency vs Number of iterations when minimum system requirement is 200kpbs, per subchannel peak power, $P_{k,n}^{peak}$ = 10mW, per user max power,P_k^{max} = 200mW.

simulation and each algorithm is run several times. The developed APASO is observed to converge faster than PSO and ACO. The pheromone guided nature of APASO improves the convergence of the algorithm towards better fitness values being reached faster.

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Paper B

Biological Resource Allocation Algorithms for Heterogeneous Uplink PD-SCMA NOMA Networks

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Abstract

Due to their ability to multiplex users on a resource element (RE), Non-orthogonal multiple access (NOMA) techniques have gained popularity in 5G network implementation. The features of 5G heterogeneous networks have necessitated the development of hybrid NOMA schemes combining the merits of the individual NOMA schemes for optimal performance. The hybrid technologies on 5G networks make complex air interfaces resulting in new resource allocation (RA) and user pairing (UP) challenges aimed at limiting the multiplexed users interference. Furthermore, common analytical techniques for evaluating the performance of the schemes lead to unrealistic network performance bounds necessitating alternative schemes. This work explores the feasibility of a hybrid power domain sparse code non-orthogonal multiple access (PD-SCMA). The scheme integrates both power and code domain multiple access on an uplink network of small cell user equipments (SUEs) and macro cell user equipments (MUEs). Alternative biological RA/UP schemes; the ant colony optimization (ACO), particle swarm optimization (PSO) and a hybrid adaptive particle swarm optimization (APASO) algorithms, are proposed. The performance results indicate the developed APASO outperforming both the PSO and ACO in sum rate and energy efficiency optimization on application to the PD-SCMA based heterogeneous network.

1 Introduction

Non-orthogonal multiple access (NOMA) has emerged as a viable candidate for 5G access network protocols. Normally, Orthogonal multiple access (OMA) schemes have exclusivity constraints when allocating users to a resource element (RE) namely; timeslot for frequency division multiple access (FDMA), subcarrier frequency for orthogonal frequency division multiple access (OFDMA) and spreading code for code division multiple access (CDMA) based schemes. The significance of NOMA is co-multiplexing users on the same spectrum resource elements (SREs) via power domain (PD) or code domain (CD) at the transmitter and successfully separating them at the receiver by multi-user detection (MUD) schemes. This culminates in enhanced spectral efficiency when compared to conventional OMA techniques. NOMA schemes permit controllable interference by non-orthogonal resource allocation albeit increase in receiver complexity [1]. However, the multiplexing of multiple users on limited REs results in cross-tier and inter-tier interference for heterogeneous networks necessitating the development of new optimal radio resource allocation (RRA) algorithms to alleviate the user pairing problems.

Two main classes of NOMA are identified as [2]; power domain NOMA (PD-NOMA) and code domain NOMA (CD-NOMA). In PD-NOMA, different power levels based on each user's channel quality conditions are used to multiplex multiple users on the same time-frequency resources. At the receiver of PD-NOMA, users are distinguished by their power levels using successive interference cancellation (SIC). CD-NOMA is grounded on classic CDMA principles that apply sparse spreading sequences or non-orthogonal low cross-correlation sequences. In [3], multiple NOMA schemes based on low density spreading (LDS) sequences such as sparse code multiple access (SCMA), multi-user shared access (MUSA), pattern division multiple access (PDMA) are presented. Among various NOMA schemes SCMA exhibits improved link-level performance compared to other code domain methods [4]. In [5], the performance of two NOMA schemes (PD-NOMA and SCMA) is compared. Considering resource allocation in heterogeneous network scenarios for both multiple access (MA) techniques, SCMA is observed to outperform PD-NOMA. A joint RRA and SIC ordering algorithm is proposed for downlink power domain sparse code multiple access (PSMA) based wireless networks [6]. Matching theory and sub-modularity principles are applied to maximize sum-rate over codebook assignment. An investigation of RRA in multiple input multiple output (MIMO)-SCMA in cloud radio access networks is done in [7]. Beamforming, joint codebook allocation and user association are separately implemented to solve the developed sum-rate maximization optimization problem. To further improve the performance of the traditional NOMA schemes and optimize their performance on heterogeneous networks by combining their individual merits, hybrid schemes are required. This work proposes a hybrid NOMA scheme that integrates PD-NOMA and SCMA on the uplink of the 5G heterogeneous network called power domain SCMA (PD-SCMA). The feasibility of such a system, especially so the development of a hybrid-generalized-SIC (HG-SIC) receiver that combines both power and code diversity, the RRA schemes and the pairing of both MUEs and SUEs, on such a hybrid access technology network, is a challenging task that needs to be undertaken.

Mathematical based algorithms have been applied for resource allocation in SCMA NOMA networks [2]. There are numerous works that have solved the resource allocation (RA) problem in SCMA using analytical Lagrangian optimization based approach. This generally involves defining the Lagrange function and solving the corresponding dual problem. Lagrangian optimization can provide optimal solutions although it is mathematically rigorous. One of the challenges of Lagrangian optimization is the difficulty that arises when dealing with non-convex problems which usually requires relaxation to be transformed into convex problems leading to approximate boundary solutions. More accurate alternative methodologies are required, hence the proposal of applying biologically inspired algorithms. Biologically inspired algorithms are seldom applied for RA in NOMA, despite the fact that they can provide optimization solutions in NOMA networks. Their adaptive characteristic makes them appropriate for the constantly changing wireless network conditions. Meta-heuristic algorithms have the advantage of simple implementation once optimization solutions can be formulated into the algorithms' framework. However, it can be challenging to represent feasible solutions into meta-heuristic algorithm structures.

Ant colony optimization (ACO) [8] emulates the behaviour of ants rummaging for food in nature. During their searching expeditions ants communicate with each other using indirect communication, referred to as "stigmergy". They accomplish this by leaving *pheromone* trails for other ants to follow towards food sources. The paths generated by ants during their tours represent potential solutions to the optimization problem. ACO has an inherent parallel and positive feedback mechanism which makes it attractive for finding user multiplexing in NOMA. Random tours in the beginning of the algorithm can reduce its performance. Introduced in [9], Particle swarm optimization (PSO) is based on simple social interaction of birds. Birds often search for food as a swarm and communicate information regarding their findings within the flock to maximize their discoveries. In PSO, particles represent potential solutions to the optimization problem. Due to its simple implementation and efficiency in solving continuous problems, PSO is attractive for enabling sharing of resources in NOMA. Biological optimization algorithms can be effective in procuring solutions to non-convex problems that often arise in RA in SCMA. To our knowledge there is limited work on the application of biological optimization methods in literature for uplink SCMA NOMA RA except the work in [10] .

The proposed PD-SCMA for 5G networks enables a new transmission policy that allows more than two MUEs and FUEs to be co-multiplexed over the same RE. The developed HG-SIC receiver combines both the power and diversity (patterns) gain in MUD. The scheme jointly optimizes the combinatorial problem of subchannel assignment and power allocation to maximize the overall system energy efficiency (EE) of the small cells. Power resources are chosen as the fundamental multiplexing domain between the MUEs and SUEs, and code domain as the key multiplexing domain in the sparse code multiplexing of the SUEs. The complexity of the system requires alternative RA algorithms. The work then develops alternative metaheuristic Biological RRA based on ant colony optimization and particle swarm optimization for optimizing EE resource allocation in hybrid heterogeneous networks (HetNets). The performance of this algorithms is compared to the analytical Lagrangian based approach [11], which provides upper performance bounds and can easily result in system design parameter overestimation.

The rest of the paper is organized as follows: Section II outlines related work on EE RA in SCMA and previous hybridization applications of the above mentioned algorithms. Section III describes the system model to be adopted in the paper, and Section IV shows how the EE problem is formulated.

Section V develops the RA and encoding. The application of RA algorithms is outlined in Section VI with the receiver algorithm developed in Section VII.Section VIII evaluates the performance of the algorithms and Section IX concludes the paper.

2 Related Work

Mathematical based resource allocation methods have been studied in previous works. Research on codebook based RA for uplink SCMA with the objective of optimizing subcarrier and power allocation to maximize total sum-rate is conducted in [2]. The derived optimization problem is solved using a matching algorithm. RA for NOMA adopting game theory approaches is presented in [12]. A user subchannel soap matching algorithm is proposed to solve the RA problem. Game theory based uplink power control (PC) in a NOMA system consisting of two interfering cells is done in [13]. A distributed PC algorithm is developed and proven to converge to the Nash equilibrium. Power minimization efforts for NOMA are done in [14]. Solutions to the considered NP-hard optimization problem are derived through relaxation and application of convex methods. Work on RA in SCMA enabling ultra reliable low latency communications is considered in [15]. With the aim of maximizing transmit rate assuming finite block-length codes, the optimization problem is solved using Lagrangian based methods and an iterative algorithm implemented. A comparison of the mathematical lagrangian based algorithms to the biologically inspired algorithms for a NOMA based HetNet has not been done in literature. Adaptive codebook design and allocation in energy saving SCMA networks is presented in [16]. Joint codebook assignment followed by power allocation is then applied. Uplink contention based SCMA for 5G networks is studied in [17]. System-level solutions are derived for UL SCMA networks in 5G radio access scenarios.

PSO application in maximizing energy efficiency subject to minimal sum-rate requirement on an uplink multi-user SCMA system is done in [10]. The non-convex EE maximization problem is solved using cooperative coevolutionary particle swarm optimization (CCPSO) algorithm. A power allocation algorithm based on PSO for application on downlink NOMA systems is developed in [18]. A fitness function is defined for energy efficiency and its performance evaluated through simulations. A PSO motivated power allocation technique for downlink NOMA IoT enabled systems is presented in [19]. The performance of the designed PSO approach is compared to conventional PA methods such as equal power allocation and water-filling. User-pairing schemes employing PSO based methods are investigated in [20]. The considered channel-aware strategies enable transmitters to minimize transmit power for multiplexed users while satisfying minimum QoS constraints for all users. A dynamic spectrum allocation method involving an enhanced PSO with mutation properties is outlined in [21]. The applied PSO is utilized to solve the non-convex power and rate optimization problem that arises. The application of PSO on NOMA based HetNets has rarely been done.

Generally, in different fields, ACO application in rate adaptive RA with proportional fairness using ACO is done in [22]. ACO is applied to solve the subcarrier allocation and sub-optimal power allocation subsequently implemented. An ACO approach to solve project scheduling problems is given in [23]. A two-pronged pheromone updating and evaluation mechanism is implemented for ants to find new solutions. In [24], parameters of an ACO algorithm are optimized in the travelling salesman problem (TSP) applications. An example of the application of hybrid ACO and PSO to optimize workflow scheduling in a cloud environment is demonstrated in [25]. The proposed method is aimed at minimizing overall workflow-time and reducing costs. A hybrid heuristic algorithm composed of PSO and ACO is conceived for task scheduling scenarios in fog computing smart production lines in [26]. The proposed technique is targeted at enhancing the energy efficiency of resource limited devices with high power consumption. Hybrid ACO based algorithms for NOMA based networks have been implemented in seldom.

For general RA in NOMA mainly on the downlink, a unified framework that examines the energy efficiency of an SCMA low complexity algorithm is investigated in [4]. Optimization of RA in dual-hop relays for multi-user SCMA is studied in [11] with a two-step joint codebook and power allocation subsequently presented. An RA strategy for SCMA based downlink system with the aim of maximizing system throughput is outlined in [27]. Proportional fair (PF) and modified largest weighted delay first algorithm (M-LWDF) are applied to solve the optimization problem. Regarding RA on the uplink, spectrum sharing between LTE and SCMA for resource allocation is conducted in [28]. Heuristic algorithms with a target of maximizing overall attainable data rate are implemented. Device-to-device (D2D) communication in uplink SCMA targeting sum-rate maximization is considered in [29]. A low-complexity two-step algorithm combining heuristic and inner approximation method is employed to solve the optimization problem. In [30], spectral efficiency in uplink SCMA considering channel state information (CSI) estimations is presented. An application of SCMA to wireless multicast communication to increase multicast capacity is done in [31]. A sub-optimal algorithm that handles power and codebook assignment separately is then proposed. Efforts to maximize sum-rate and fairness in uplink SCMA using joint channel and power are illustrated in [32]. Iterative algorithms that jointly allocate codebooks and transmit power in subcarriers are implemented with convex programming used to optimize performance. In [33], a power domain SCMA in which the power domain and code domain NOMA paradigms are combined in transmitting multiple user signals over a subcarrier on the downlink is presented. SCMA codebooks are reused by multiple users employing power domain NOMA (PD-NOMA) to transmit signals non-orthogonally. A joint power domain and SCMA downlink system is also developed in [34]. MPA combined with SIC is implemented in the receiver. A network model that applies hybrid PD-SCMA technology to a two tier HetNet uplink featuring MUEs and SUEs user pairing with cross tier interference has not been developed.

There is limited work on the application of ant colony optimization and particle swarm optimization and their hybrids in resource allocation on power domain sparse code multiple access networks. Thus, the focus of this work is to develop hybrid power domain SCMA optimization problem framework, investigate the application of metaheuristic algorithms (ACO and PSO and a developed hybrid) resource allocation, compare the performance of the proposed algorithms to the analytical Lagrangian based optimization which shows possibilities of system overestimation.

3 System Model

The network model is a two-tier HetNet consisting of a centralised single macro base station (MBS) uniformly populated by a set of $S_i = \{1, 2, \dots, F\}$ centralised small cell base stations (SBSs) and M MUEs as in Figure B.1. Each of the F small cells is populated with K uniformly distributed SUEs.

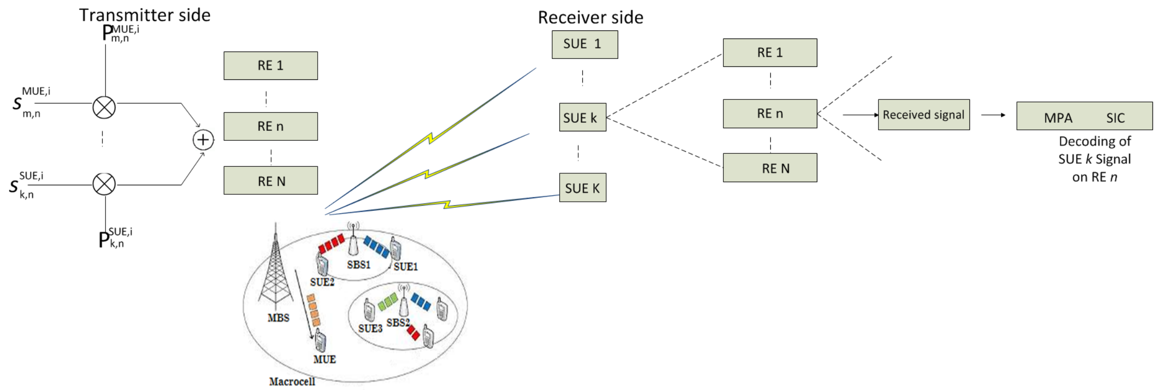

Fig. B.1: System model

As in [2], it is assumed an SUE is represented as an SCMA layer and each user is assigned a RE. The REs are shared among SUEs while MUEs are co-multiplexed over the same time-frequency resources using PD-NOMA. In the uplink HetNet model, REs can be reused between MUEs and SUEs in small cells as PD-NOMA is coupled with SCMA in MUE communication, while only SCMA is employed in small cells.

The network total bandwidth B, is divided into N REs occupying a bandwidth $B_{sc} = B/N$. The transmitter assigns power level, $P_{k,n}^{SUE,i}$, to the the k^{th} SUE in i^{th} SBS on the n^{th} RE and also allocates transmit power, $P_{m,n}^{MUE,i}$, to the m^{th} MUE associated with in i^{th} SBS on the n^{th} RE. Let $h_{k,n}^{SUE,i}$ and $h_{m,n}^{MUE,i}$ denote the channel gain of the k^{th} SUE to the i^{th} SBS on the n^{th} RE, and the channel gain of the m^{th} MUE on the n^{th} RE associated with the i^{th} SBS. Define $V_{K,N}^{SUE,I} = [\mu_{k,n}^{SUE,i}]_{F\times K\times N}$ as the RE HG-NOMA transmitter RE matrix for small cells where $\mu_{k,n}^{SUE,i} = 1$ implies that the k^{th} SUE connected to the i^{th} SBS has been assigned the n^{th} RE. In a similar manner, $V_{M,N}^{MUE,I}$ can also be defined such that $V_{M,N}^{MUE,I} = [\mu_{k,n}^{MUE,i}]_{M\times N}$ as the HG-NOMA RE matrix where $\mu_{k,n}^{MUE,i} = 1$ means that the n^{th} RE has been allocated to the m^{th} MUE in the i^{th} SBS . Based on the hybrid power domain SCMA paradigm following the work in [33], the received signals can be detected using MPA and SIC. This consideration allows for the reuse of REs among MUEs and SUEs.

Focusing on the small cell network, the received signal of the k^{th} SUE on the n^{th} RE in the i^{th} SBS, $y_{k,n}^{SUE,i}$, after SUEs multiplexing is expressed as

$$y_{k,n}^{SUE,i}(t) = \underbrace{V_{k,n}^{SUE,I}(\sqrt{P_{k,n}^{SUE,i}}h_{k,n}^{SUE,i}s_{k,n}^{SUE,i})}_{\text{Desired signal}} + \underbrace{\sum_{j\neq k}^{K} V_{j,n}^{SUE,I}(\sqrt{P_{j,n}^{SUE,i}}h_{j,n}^{SUE,i}s_{j,n}^{SUE,i})}_{I_{k,n}}$$
$$+ \underbrace{\sum_{m=1}^{M} V_{m,n}^{MUE,I}(\sqrt{P_{m,n}^{MUE,i}}h_{m,n}^{MUE,i}s_{m,n}^{MUE,i})}_{I_{CT}} + w_{i,k,n}, \quad \text{(B.1)}$$

where $s_{k,n}^{SUE,i}$ is the k^{th} SUE message symbol on the n^{th} RE in i^th SBS, $s_{m,n}^{MUE,i}$ is the message symbol of the m^{th} MUE on the n^{th} RE affiliated with the i^{th} SBS. $I_{k,n}$ is the intra-tier interference and I_{CT} denotes the cross-tier interference from the M MUEs. $w_{i,k,n}$ is the noise vector modelled as Additive Gaussian White Noise (AGWN). The RE matrices $V_{K,N}^{SUE,I}$ and $V_{K,N}^{MUE,I}$ are determined in Section V. It is assumed that each base station has perfect knowledge of channel state information (CSI).

4 Problem Formulation

The signal to noise-plus interference (SINR) of k^{th} SUE in i^{th} SBS using n^{th} RE, $\Gamma_{k,n}^{SUE,i}$, is given by

$$\Gamma_{k,n}^{SUE,i} = \frac{V_{k,n}^{SUE,I}P_{k,n}^{SUE,i}|h_{k,n}^{SUE,i}|^2}{I_{k,n} + I_{CT} + E\{|\sigma|^2\}}, \quad \text{(B.2)}$$

where σ^2 is the additive white gaussian noise (AWGN). The upper bound of the attainable sum rate of each user can be expressed as

$$R_{k,n}^{SUE,i} = log_2(1 + \Gamma_{k,n}^{SUE,i}). \quad \text{(B.3)}$$

The total rate of the system can be expressed as

$$R_{tot} = \sum_{i=1}^{F}\sum_{n=1}^{N}\sum_{k=1}^{K}\mu_{k,n}^{SUE,i} log_2(1 + \Gamma_{k,n}^{SUE,i}), \tag{B.4}$$

The total power, P_{tot}, consumed by the system can be written as

$$P_{tot} = \sum_{i=1}^{F}\sum_{k=1}^{K}\sum_{n=1}^{N} P_{k,n}^{SUE,i} + KP_{sta}, \tag{B.5}$$

where P_{sta} is the SUEs static power. The energy efficiency, η_e, of the system is defined as [10]

$$\eta_e = \frac{R_{tot}}{P_{tot}}. \tag{B.6}$$

Therefore, the energy efficiency optimization problem considering minimum rate requirements can be formulated as

$$\max_{V_{k,n}^{SUE,I}, P_{k,n}^{SUE,i} \geq 0} \{\eta_e(R_{tot}, P_{tot})\}, \tag{B.7}$$

subject to :

$$C1 : \sum_{i=1}^{F}\sum_{k}^{K}\sum_{n=1}^{N}\mu_{k,n}^{SUE,i} R_{k,n}^{SUE,i} \geq R_{k,n}^{min},$$

$$C2 : \sum_{n=1}^{N}\mu_{k,n}^{SUE,i} P_{k,n}^{SUE,i} \leq P_{max},$$

$$C3 : P_{k,n}^{SUE,i} \geq 0,$$

$$C4 : \sum_{i=1}^{K}\mu_{k,n}^{SUE,i} + \sum_{i=1}^{M}\mu_{k,n}^{MUE,i} \leq d_f,$$

$$C5 : \sum_{i=1}^{K}\mu_{k,n}^{SUE,i} + \sum_{i=1}^{M}\mu_{k,n}^{MUE,i} \leq d_s,$$

$$C6 : \mu_{k,n}^{SUE,i} or \mu_{k,n}^{MUE,i} \in \{0, 1\},$$

$R_{k,n}^{min}$ in $C1$ is the minimum system sum-rate required for the SUEs, P_{max} in $C2$ is the maximum transmit power of SUEs, d_f in $C4$ is the degree of RE which means that a RE can be used at most by d_f users, $C5$ implies that the maximum number of REs utilized by each user is d_s, set to d_s = 3 in this work to minimize receiver complexity.

5 Resource Allocation and Encoding

5.1 Power Allocation

To allocate power to SUEs, a well established method of water-filling [35] is adopted due to its simple implementation. Assuming initial minimum power allocation level, let $\{\tilde{h}_{k,n}^{SUE,i}\}$ be a sorted sequence of channel gains which is positive and monotonically decreasing. Define d_i as the step depth written as $d_i = \frac{1}{\tilde{h}_{k,n}^{SUE,i}}$, for $i = 1, 2, \ldots, N$, where N is the number of channels. Then the step depth difference, $\delta_{i,j}$, can be expressed as

$$\delta_{i,j} = d_i - d_j = \frac{1}{\tilde{h}_{k,n}^{SUE,i}} - \frac{1}{\tilde{h}_{k,n}^{SUE,j}} (1 \leq i, j \leq N), \tag{B.8}$$

The power allocation vector level, $P_{k,n}^{SUE,i}$, can be obtained using [35]

$$P_{k,n}^{SUE,i} = \left\{ P_{max} - \sum_{i}^{N-1} \delta_{i,j} \right\}^{+}. \tag{B.9}$$

The implemented power allocation is shown in Algorithm 5.

Algorithm 5: Water-filling based Power Allocation

Input: N, P_{max}
Output: $P = \{P_{k,n}^{SUE,i} | \forall i \in N\}$
Initialize minimum power allocation, $P_{k,n}^{SUE,i}$, across REs
for *i=1:F* **do**
    for *k=1:K* **do**
        for *n=1:N* **do**
            Sort SUEs based on their channel conditions, equation (B.2)
            Update power allocation vector P using equation (B.8), (B.9)
        end
    end
    Continue process until convergence reached or number of iterations exceeded.
end

5.2 SCMA Encoding

The encoding where REs are mapped to a set of C codebooks with the number of codebooks that can be generated determined as $C = \binom{L}{J}$ is used [3], [33]. The SCMA encoding process in which $log_2 Q$

binary bits are mapped to L-dimensional codewords of size Q is illustrated in Figure B.2. Each codebook is assumed to contain Q codewords with length L which are transmitted over orthogonal radio resources (such as OFDMA subcarriers). The L-dimensional codewords that constitute a codebook are sparse vectors with J non-zero entries where $J < L$. In this scenario, the overloading factor can be defined as $\lambda = K/L$. For the k^{th} SUE on the n^{th} RE in i^{th} small cell ($SUE^i_{k,n}$), and the m^{th} macro cell user on n^{th} RE in the proximity of i^{th} small cell ($MUE^i_{m,n}$), a codebook is allocated with codebook reuse being allowed as in [33]. As codebooks are transmitted on different wireless channels , the MPA receiver can still recover the data streams without collisions. Codebook reuse can improve both the overloading factor and the number of connections to enable massive connectivity. Optimal SCMA decoding is achieved using the maximum a priori (MAP) decoding [36] but the message passing algorithm (MPA) which offers approximate performance at reduced decoding complexity is considered in this work.

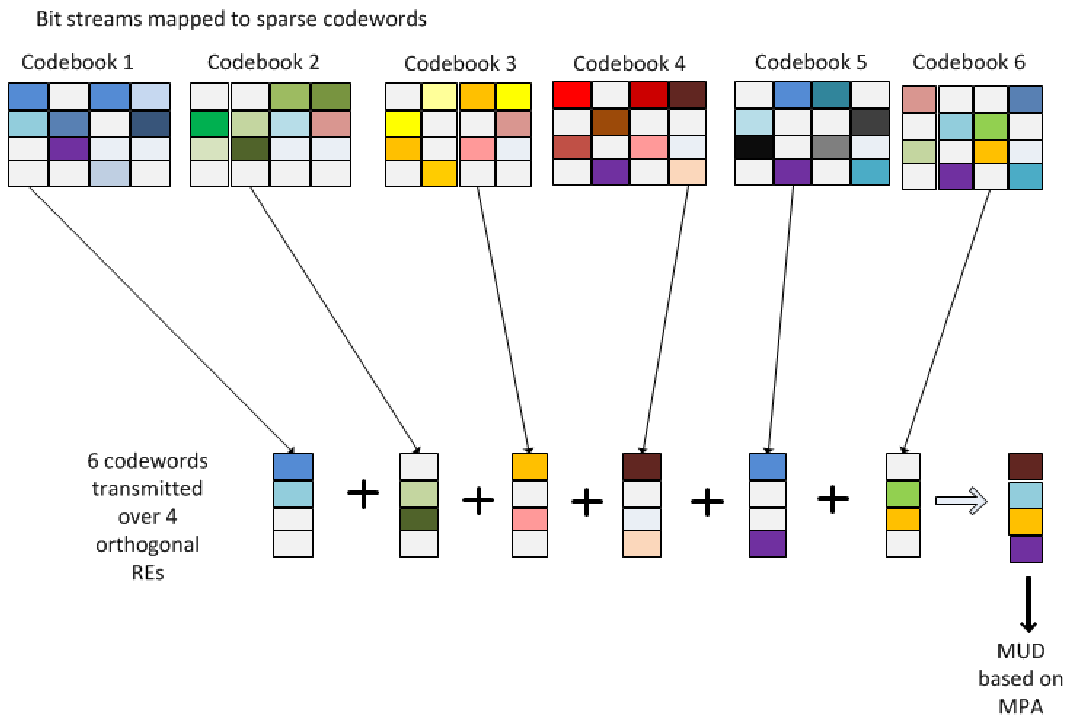

Fig. B.2: Example of SCMA encoding with K=6 SUEs,L=4 REs, J=2

5.3 Resource Allocation

Consider the scenario where the k^{th} user is allocated a maximum of d_s REs (equation B.7 $C5$). Let the UE-to-RE matrix, A_k, be a $N \times d_s$ matrix where rows represent REs in the system. To preserve the sparsity of SCMA, there is only one non-zero entry in each column of A_k which corresponds to the RE designated to the k^{th} user. For instance, if $d_s = 2$, $N = 4$, and user 1 is allocated the first and third REs, its spreading matrix could be expressed as

$$A_1 = \begin{bmatrix} 1 & 0 \\ 0 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix}. \tag{B.10}$$

For K users in the system, the corresponding SCMA spreading matrix of size $N \times (Kd_(s))$ is given by

$$A_k^N = [A_1, A_2, \ldots, A_K]. \tag{B.11}$$

In (B.11), the columns are derived in the following manner. The columns belonging to the k^{th} user are in the range $(k-1)d_s + 1$ to kd_s. For example, an SCMA system with $K = 6$, $N = 4$, $d_s = 2$ operating at full-load could have the following spreading matrix,

$$A_N^K = \begin{bmatrix} 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \end{bmatrix}. \tag{B.12}$$

Having derived the spreading matrix in (B.12) UE-RE correlation can be encapsulated in a factor matrix defined as $F_k^n = [f_1, f_2, \ldots, f_K]$, where $f_k^n = 1$ implies that k^{th} UE occupies n^{th} resource element and $f_k^n = 0$ means no resources have been assigned. The elements of the factor matrix are computed from $f_k = diag(A_k A_k^T)$. Consequently, the factor matrix for the previous example in (B.12) is given by

$$F_k^n = \begin{bmatrix} 1 & 0 & 1 & 0 & 0 & 1 \\ 0 & 1 & 1 & 0 & 1 & 0 \\ 1 & 0 & 0 & 1 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 & 1 \end{bmatrix}. \tag{B.13}$$

The first column of F_k^n represent the first UE is allocated the first and third REs. Similarly, the second UE is assigned the second and fourth REs as shown in the second column of F_k^n, and the rest of the UEs are assigned as illustrated in the remaining columns of F_k^n. The first row represents the first RE which is utilized by the first, third and sixth UEs. The UE-RE scheduling vector,V_{sc}^n, can be succinctly written as

$$V_{sc}^n[RE] \Leftrightarrow [UE_1, UE_2, \ldots, UE_K], \tag{B.14}$$

where UE_k is allocated a set of d_s REs based on the root mean square (RMS) values of the channel gains. Note that the RA matrices $V_{k,n}^{SUE,I}$ and $V_{k,n}^{MUE,I}$ of Section III are a subsets of $V_{sc}^n[RE]$.

6 Applicaiton of RA Algorithms

The conventional application of the lagrangian method in optimization of (B.7) is as in [37]. In the alternative algorithms, user to RE pairing is performed using biological algorithms based on channel conditions. At the beginning of the RA process, the biological algorithms embark on a random search for UE to RE pairs based on SINR conditions. The random explorations are utilized to initialize the algorithms in their respective frameworks. Considering the constantly changing wireless channel conditions, the adaptive nature of the biological algorithms is exploited to discover channels in which UEs have better SINR so as to maximize the data rate at minimum transmit power.

6.1 Lagrangian Based Optimization

The optimization problem in (B.7) is a non-convex problem that needs to be transformed using nonlinear fractional programming Dinkelbach approach [37] before it can be solved using convex based techniques such as Lagrangian optimization. The optimization problem in (B.7) can be re-written as

$$\max_{\mu_{k,n}^{SUE,i}, P_{k,n}^{SUE,i} \geq 0} \{R_{tot} - \eta_e(P_{tot})\}, \tag{B.15}$$

It can be proven that the optimal solution of the subtractive form of the optimization problem in (B.15) is reached when $R_{tot} - \eta_e(P_{tot})\}$ approaches zero. If the objective function in (B.7) has undergone transformation to reduce the non-convex complexity by assuming the binary variable $\mu_{k,n}^{SUE,i}$ to be continuous, then the Lagrangian function can be expressed as

$$\begin{aligned} L(R, P, \eta_e, \Omega) = R_{tot} - \eta_e(P_{tot})\} \\ - \lambda(\sum_{n=1}^{N} \mu_{k,n}^{SUE,i} R_{k,n}^{SUE,i} - R_{k,n}^{min}) - \gamma(\sum_{j=1}^{J} \mu_{k,n}^{SUE,i} - d_f) \\ - \alpha(\sum_{k=1}^{K} \mu_{k,n}^{SUE,i} - d_s) - \beta(P_{max} - \sum_{n=1}^{N} \mu_{k,n}^{SUE,i} P_{k,n}^{SUE,i}), \end{aligned} \tag{B.16}$$

where $\Omega = (\lambda \geq 0, \gamma \geq 0, \alpha \geq 0, \beta \geq 0)$ are Lagrange multipliers for relaxed constraints. Constraints in $C3$ and $C6$ are absorbed by Karush-Kuhn-Tucker (KKT) conditions. The dual function can be defined as

$$g(\eta_e, \Omega) = \max_{R_{k,n}^{SUE,i}, P_{k,n}^{SUE,i}} L(P, R, \eta_e, \Omega), \tag{B.17}$$

The dual problem can correspondingly be expressed as

$$\min_{R_{k,n}^{SUE,i}, P_{k,n}^{SUE,i}} \quad g(\eta_e, \Omega), \tag{B.18}$$

In solving the Lagrangian function, (B.16) is decomposed into a master problem and $K \times N$ subproblems. The solution of each subproblem is derived by iteratively solving the subproblem in the corresponding SBS. The equation in (B.16) can be written as

$$L_(R, P, \eta_e, \Omega) = L_{in} + \lambda(R_{k,n}^{min}) - \gamma(d_f) - \alpha(d_s) - \beta(P_{max}), \tag{B.19}$$

where

$$L_{in} = \sum_{n=1}^{N} \mu_{k,n}^{SUE,i} R_{k,n}^{SUE,i} + \sum_{k=1}^{K} \eta_e P_{k,n}^{SUE,i} \\ - \lambda(R_{k,}^{SUE,i}) - \gamma d_f - \alpha(d_s) - \beta(P_{k,n}^{SUE,i}). \tag{B.20}$$

Optimal transmit power is obtained by applying KKT conditions in combination with optimization methods,

$$P_{k,n}^{SUE,i} = \frac{B_{sc}(1+\gamma)}{\sum_{j \neq k}^{K} B_{sc}(1+\gamma)(\Gamma_{j,n}^{SUE,i}) + ln2(\lambda + \chi_{k,n}^{MUE,i})}, \tag{B.21}$$

where $\chi_{k,n}^{MUE,i} = \mu_{k,n}^{MUE,i} h_{k,n}^{MUE,i}$. The subgradient method is employed to update Lagrangian dual variables as follows

$$\lambda^{t+1} = \lambda^t - \zeta_1^t \Big[R_{k,n}^{SUE,i} - R_{k,n}^{min} \Big]^+, \tag{B.22}$$

$$\beta^{t+1} = \beta^t - \zeta_2^t \Big[P_{max} - \sum_{n=1}^{N} \mu_{i,k,n} P_{k,n}^{SUE,i} \Big]^+, \tag{B.23}$$

where ζ_1^t and ζ_2^t are step sizes of iteration $t \in \{1, 2, \ldots, I_{max}\}$. When the step sizes are sufficiently small, the Lagragian multipliers converge to equilibrium points. The implemented scheduling algorithm is as outlined in Algorithm 6.

6.2 Particle Swarm Optimization(PSO)

6.2.1 Principle of Operation

In the basic PSO [9], a particle represents a viable solution to the objective function $F(x)$ where x is the decision vector in D dimensional search space. The i^{th} particle position in the search space can be expressed as a position vector $x_i = [x_{i1}, x_{i2}, \ldots, x_{iD}]$ which roves in the search space with velocity $v_i = [v_{i1}, v_{i2}, \ldots, v_{iD}]$. As particles traverse the search space, a fitness function (f) related to $F(x)$ is evaluated for each particle and the positions of highest personal fitness values of particles, f_{pbest}, and

Algorithm 6: Lagrangian PD-SCMA Resource Scheduling

Input: Maximum number of iterations, I_{max}
Initialize maximum number of iterations I_{max} Initialize energy efficiency η_e and equal power allocation,$P_{k,n}^{SUE,i}$ across REs
while *(convergence not reached or maximum iterations exceeded)* **do**
    for *i=1:F* **do**
        for *n =1:N* **do**
            Initialize Lagrange multipliers $(\lambda, \gamma, \alpha, \beta)$
            Given η_e, compute $P_{k,n}^{SUE,i}$ equation (B.21) ,
            Update available resources, equation (B.7) $(C5\&C6)$,
            Determine the throughput, equation (B.4),
            Update Lagrange multipliers according to (B.22), (B.23),
            Continue process until convergence reached or number of iterations exceeded.
        end
    end
end

the best fitness value of the entire swarm, f_{gbest}, are stored. Given a swarm of P_n particles, with the personal best values, $P_{i,f_{pbest}}$, and global best value, $P_{i,f_{gbest}}$, of the particles can be expressed as

$$P_{i,f_{pbest}} = arg \quad min[f_{pbest}, x_{id}], \tag{B.24}$$

$$P_{i,f_{gbest}} = arg \quad min[f_{gbest}, x_{id}], \tag{B.25}$$

Particles instantaneously update their velocity vector to attain their previous best fitness and migrate towards the swarm's global best fitness value. Each i^{th} particle's d^{th} dimension has velocity, v_{id}^{t+1}, calculated according to

$$v_{id}^{t+1} = wv_{id}^{t} + c_1 r_1 (P_{i,f_{pbest}} - x_{id}^{t}) + c_2 r_2 (P_{i,f_{gbest}} - x_{id}^{t}), \tag{B.26}$$

where w is particles inertia, $P_{i,f_{pbest}}$ is the personal best position of the particle, c_1 and c_2 are personal and social learning factors respectively. The variables r_1 and r_2 are random values normally in the range 0 to 1. Particles' d^{th} dimension position is updated as

$$x_{id}^{t+1} = x_{id}^{t} + v_{id}^{t+1}, \tag{B.27}$$

where v_{id} is the velocity vector with an equivalent dimension as the position vector. The dimensions of the search space varies based on the nature of the optimization problem under consideration. Information pertaining to particles' current positions and their personal bests is stored in matrices X_p and Y_p respectively.

$$X_p = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,F} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,F} \\ \vdots & \vdots & \ddots & \vdots \\ x_{sk,1} & x_{sk,2} & \cdots & x_{sk,F} \end{bmatrix}, \tag{B.28}$$

$$Y_p = \begin{bmatrix} y_{1,1} & y_{1,2} & \cdots & y_{1,F} \\ y_{2,1} & y_{2,2} & \cdots & y_{2,F} \\ \vdots & \vdots & \ddots & \vdots \\ y_{sk,1} & y_{sk,2} & \cdots & y_{sk,F} \end{bmatrix}. \tag{B.29}$$

The i^{th} row of X_p is a F-dimensional vector concatenating all current position vectors x_i from K particles.

6.2.2 PSO RE scheduling

In application of PSO to SCMA RA, particles represent feasible solutions to the RE scheduling optimization problem which involves codebooks assignment to users. The fitness function, $F(x)$, is the energy efficiency optimization problem of equation (B.7) expressed as

$$F(x) \Leftrightarrow max\{\eta_e(R, P)\}. \tag{B.30}$$

As particles traverse the search space to discover UE-RE assignments which yield good energy efficiency solutions, they evaluate the fitness function of equation (B.30). A particle in this instance represents the multiplexing of K SUEs using L-dimensional codewords over N subcarriers to solve the optimization problem of equation (B.7) with the associated constraints. In every Transmission Time Interval (TTI), the position of each particle, x_{id} represents a feasible RE assignment and is constructed to form the resource scheduling vector defined as a position vector $x_{id} = [x_{i1}, x_{i2}, \ldots, x_{iN}]$,

$$x_{id} \Leftrightarrow V_{sc}^{n}[RE], \tag{B.31}$$

where $V_{sc}^{n}[RE]$ is given by equation (B.14). Particles then update their personal best positions which corresponds to the best scheduling solution the particle has discovered thus far. The global best particle position is updated if the personal best of the particle at that instant is detected to be better than the current global best position. The implemented scheduling algorithm is outlined in Algorithm 7.

Algorithm 7: PSO PD-SCMA Resource Scheduling

Input:
UEs: U = { 1,...,k,...,UE_K }
REs: R = {1,...,n,... RE_N }
Initialize: c_1, c_2, r_1, r_2, w
while *(convergence not reached)* **do**
  for *i=1:F* **do**
    for *n =1:N* **do**
      Generate random positions of particles and store them, equation (B.27) & (B.28).
      Perform RA, equation (B.14) ,
      Update available resources, equation (B.7) ($C5$&$C6$),
      Determine the throughput, equation (B.4),
      Allocate power, Algorithm 1,
      Evaluate particle fitness, equation (B.30),
      Update,f_{pbest}, equation (B.24)& (B.29),
      if $P_{i,f_{gbest}}$ > $P_{i,f_{gbest}}$ **then**
        Update, $P_{i,f_{gbest}}$, equation (B.25) ,
      end
      Allocate power, Algorithm 5,
      Continue process until convergence is reached or number of iterations exceeded.
    end
  end
end

6.3 Ant Colony Optimization (ACO)

6.3.1 Principle of Operation

A typical ACO application involves modelling a discrete combinatorial optimization problem as a construction graph. The optimization problem is formulated as a graph coloring problem represented by $G = (V, E)$ where V is the number of vertices and E is the number of edges. In the Ant Colony Optimization Assignment Type Problem (ACO ATP) [38], [39], i nodes are assigned j colors where items are assumed to be nodes on the graph and objects are represented by colors. Artificial ants generate paths which are feasible solutions as they travel through the graph. In each path, ants choose a path $P_{i,j}$ which represents an assignment of j objects to i items, and evaluate the fitness function $F_{i,j}(x)$ which is related to the objective function being optimized.

$$P_{i,j} = max\{F_{i,j}(x)\}. \tag{B.32}$$

They choose the optimal path, $P^{op}_{i,j}$, that maximizes the fitness function F^{op}_{ij},

$$P^{op}_{i,j} = max\{F^{op}_{i,j}(x)\}. \tag{B.33}$$

An ATP ACO set up often requires two probabilistic rules for choosing nodes and colors. The first probability, $p^{'}_{i,j}(t)$, for ant a choosing the next node when it is at node i, is given by

$$p^{'}_{i,j}(t) = \frac{\tau^{'\alpha}_{i,j}(t)\eta^{'\beta}_{i,j}(t)}{\sum_{j\in S^k_i(t)} \tau^{'\alpha}_{i,j}(t)\eta^{'\beta}_{i,j}(t)}, \tag{B.34}$$

where α, β are pheromone weighting factors, $\tau^{'}_{i,j}$, is the pheromone intensity, $\eta^{'}_{i,j}$ is the desirability, and $S^k_i(t)$ is set of feasible nodes from ant a at node i. The desirability of ant a choosing the next node is given by the heuristic function, $\eta^{'}_{i,j}(t)$,

$$\eta^{'}_{i,j}(t) = \frac{1 + |N^k_{unassigned}|}{1 + |N_{nei,i}|}, \tag{B.35}$$

where $|N^k_{unassigned}|$ is the number of neighbours to the current node that have not been allocated objects, and $|N_{nei,i}|$ is the number of neighbors from the perspective of the ant when at node i. The pheromone in previously chosen nodes is defined as

$$\tau^{'}_{i,j}(t) = \frac{F^{best}_{i,j}}{|N^{best}_i(t)|}, \tag{B.36}$$

where $F_{i,j}^{best}$ is the fitness function of best ant, and N_i^{best} is the set of feasible nodes from the perspective of best ant at node i. The second probability, $p_{i,o}^{''}(t)$, of choosing an object to assign for the current node from the set of objects, N_o, is given by

$$p_{i,o}^{''}(t) = \frac{\tau_{i,c}^{''\alpha}(t)\eta_{i,o}^{''\beta}(t)}{\sum_{j \in N_o} \tau_{i,c}^{''\alpha}(t)\eta_{i,o}^{''\beta}(t)}, \tag{B.37}$$

where the heuristic function, $\eta_{i,o}^{''}$, is defined as

$$\eta_{i,o}^{''}(t) = \frac{1 + n_{previous-best}}{1 + n_{available-obj}}, \tag{B.38}$$

where $n_{previous-best}$ is the number of elements in the set of previously assigned objects, $n_{available-obj}$ is the number of objects available for allocation. The pheromone, $\tau_{i,c}^{''}$, is updated using

$$\tau_{i,c}^{''}(t) = \frac{n_{previous-best}}{|N_i^{Best}(t)|}. \tag{B.39}$$

The fitness function $F_{i,j}$ of each path which represents a solution to the optimization problem is calculated along each path and paths with higher fitness have more pheromones deposited on them.

6.3.2 Ant Colony Optimization(ACO) RA scheduling

On application to SCMA RA, UEs are represented by nodes and RE allocation patterns are associated with colors. A path that represents the assignment of n REs to k UEs can be formulated from equation (B.14) as

$$P_{k,n} \Leftrightarrow V_{sc}^{n}[RE]. \tag{B.40}$$

The optimal path, $P_{k,n}^{op}$, that maximizes optimization function is

$$P_{k,n}^{op} \Leftrightarrow \widetilde{V_{sc}^{n}}[RE] \Leftrightarrow max\{F_{k,n}(x)\}. \tag{B.41}$$

The fitness function, $F_{k,n}(x)$ is given by

$$F_{k,n} = max\{\eta_e(R,P)\}. \tag{B.42}$$

As ants traverse the search space they leave pheromone in paths that have higher fitness, i.e. RE allocations that have desirable energy efficient transmission rates in their path for other ants to follow in future travels. A colony of RA scheduling decisions is build by ants based on tours in which they discovered optimal sum rates. The applied ACO SCMA resource scheduling algorithm is summarized in Algorithm 8.

Algorithm 8: ACO PD-SCMA Resource Scheduling

```
Input:
UEs: U = { 1,...,k,...,UE_K }
REs: R = {1,...,n,... RE_N }
Initialize: α , β , ρ
while ( convergence not reached) do
    for i=1:F do
        for k=1:K do
            for n =1:N do
                Begin ant search for REs in R that satisfy (B.7, C1).
                Perform RA, equation (B.14),
                Update available resources, equation B.7 (C5&C6).
                Determine the throughput, equation (B.4)
                Allocate power, Algorithm 5,
                Evaluate fitness function, equation (B.41).
                Update pheromone for higher fitness functions, equation (B.36) & (B.39).
                Continue process until convergence reached or number of iterations exceeded.
            end
        end
    end
end
```

6.4 Adaptive Particle Ant Swarm Optimization (APASO)

6.4.1 Principle of Operation

Artificial *ant particles* possessing both attributes of PSO and ACO are created and randomly initialized in the search space. For all ant particles the fitness function $F(x)$ is computed. To improve the performance of PSO a pheromone-guided mechanism is employed to indicate ant particles with more fitness. In [40], it is outlined how the inertia weight provides a balance between exploration and exploitation. Having a higher inertia weight in the beginning enables global search, while a lower inertia weight in later stages of algorithm enhances convergence towards personal and global best values. In our proposed APASO we consider the modification of ant particles inertia weight as

$$w \Leftrightarrow \tau_{inter}, \tag{B.43}$$

where τ_{inter} is the inter ant particle pheromone given by

$$\tau_{inter} = \zeta\left(\left|\frac{min(F^t_{pbest}(x), \overline{F}_t(x))}{max(F^t_{pbest}(x), \overline{F}_t(x))}\right|\right), \tag{B.44}$$

where ζ is a control parameter in the range [0,1], and $\overline{F}_t(x)$ is the mean fitness of all ant particles at t, and $F^t_{pbest}(x)$ is personal best fitness of ant particles at t. For a d-dimensional space, an ant particle has velocity, v^{t+1}_{id} and position, x^t_{id}, defined by

$$v^{t+1}_{id} = \tau_{inter} v^t_{id} + c_1 r_1 (p^t_{pb} - x^t_{id}) + c_2 r_2 (p^t_{gb} - x^t_{id}), \tag{B.45}$$

$$x^{t+1}_i = x^t_i + v^{t+1}_i, \tag{B.46}$$

where p^t_{pb} and p^t_{gb} are personal best and global best of ant particles defined similar to equations (B.24) and (B.25) respectively. In equation (B.45) applying the inter ant particle (τ_{inter}) pheromone to the first term on the right hand side of the equation enables diversity of ant particles' search in early iterations of the algorithm while increasing convergence in later iterations.

6.4.2 Adaptive Particle Ant Swarm Optimization (APASO) Scheduling

The proposed hybrid technique aims to exploit advantages of PSO and ACO to attain superior performance to the conventional algorithms. In the beginning stage of the scheduling process, PSO generates new random particle ants, and the ACO based pheromone mechanism generates pheromones for ant particles to mark solutions with higher fitness values. It is these favourable qualities of the PSO and ACO that have motivated the hybridization of PSO and ACO in the proposed APASO. The position of an ant particle is modelled as scheduling vector in a particular TTI as

$$x_{id} \Leftrightarrow V_{sc}^{n}[RE], \tag{B.47}$$

where $V_{sc}^{n}[RE]$ is defined as equation (B.14). The fitness function is formulated to solve the optimization problem in equation (B.7) as

$$F(x) \Leftrightarrow max\{\eta_e(R,P)\}. \tag{B.48}$$

Each ant particle then stores its position together with its fitness value, and keeps updating velocity in equation (B.45) so that the ant particles maintain their migration towards better solutions. The mechanics of the APASO algorithm for RE scheduling in SCMA is summarized in Algorithm 9.

Algorithm 9: APASO PD-SCMA Resource Scheduling

Input:
UEs: U = { 1,...,k,...,UE_K }
REs: R = {1,...,n,... RE_N }
Initialize c_1, c_2, r_1, r_2, w,τ_{inter} **while** *(convergence not reached)* **do**
  for *i=1:F* **do**
    for *n =1:N* **do**
      Initialize random ant particles search,
      Allocate resources, equation (B.14),
      Determine the throughput, equation (B.4),
      Distribute pheromone τ_{inter}, equation (B.44),
      Evaluate fitness function for all ant particles, equation (B.48),
      Update the velocity and position vectors for ant particles, equations (B.45) & (B.46),
      Update pheromone, equation (B.44),
      Allocate power, Algorithm 5,
      Continue process until convergence is reached or number of iterations exceeded.
    end
  end
end

7 Receiver Algorithm and Complexity

To detect and decode the received signal, the k^{th} SUE at i^{th} SBS using codebook c detects and removes signals of $d_f - 1$ users. Denoting the mean channel gains of users superimposed on codebook c as $\tilde{H}_{k,c}^{SUE,i}$, the receiver algorithm is outlined in Algorithm 10.

Algorithm 10: PD-SCMA Based Receiver

Input:
Received signal from all orthogonal subcarriers, Channel gain matrix for all users, $\tilde{H}_{k,c}^{SUE,i}$
Initialize maximum number of iterations I_{max}
Set $\tilde{H}_{k,n}^{SUE,i} = \min \tilde{H}_{k,c}^{SUE,i}$
Apply MPA on the received signal
Output $V_{k,n}^{SUE,I}(\sqrt{P_{k,b}^{SUE,i}} h_{k,n}^{SUE,i} x_{k,n}^{SUE,i})$ (SUE k signal on codebook n in i^{th} SBS).
Apply SIC on resulting signal
$y_{k,n}^{SUE,i} = y_{k,n}^{SUE,i} - (V_{k,n}^{SUE,I}(\sqrt{P_{k,b}^{SUE,i}} h_{k,n}^{SUE,i} x_{k,n}^{SUE,i})$
Set $\tilde{H}_{k,c}^{SUE,i} = \tilde{H}_{k,c}^{SUE,i} - \tilde{H}_{k,n}^{SUE,i}$
Repeat process until all SUEs data has been decoded.

Assume that a codebook in PD-SCMA is allocated to d_f users at the same time with each SUE applying MPA d_f times and implementing SIC (d_f-1) times in the process of detecting and decoding transmitted data. In the case where C codebooks are assigned to d_f SUEs, the complexity of the receiver can be approximated as

$$\mathcal{O}(I_{max}|\nu|^p(C)(d_f)), \tag{B.49}$$

where ν is the codebook size, I_{max} is the maximum number of iterations, p is the non-zero elements of factor matrix $F_k^n = f_1, \ldots, f_n$.

8 Performance Evaluation

In simulations, it is assumed that SUEs are randomly distributed in small cells which are uniformly distributed in the macrocell coverage area. The radii of the macrocell and small cells are 500m and 20m respectively, and minimum distance between the small cells and MBS is 40m. The system bandwidth is considered to be 10 MHz with the channel model assumed to characterized by small scale Rayleigh fading with large scale path loss and 8dB log-normal shadowing . The maximum transmit power is 21 dBm and $P_{sta} = 18$ dBm. The minimum data rate is assumed to be 5 Mbps.

Figure B.3 shows a plot of sum-rate vs number of users in the network. As the number of users increases the sum-rate of the system increases, although the gradient of the sum-rate curve decreases with increasing number of users. APASO offers better performance than the PSO and ACO achieving performance close to the analytical Lagrangian.

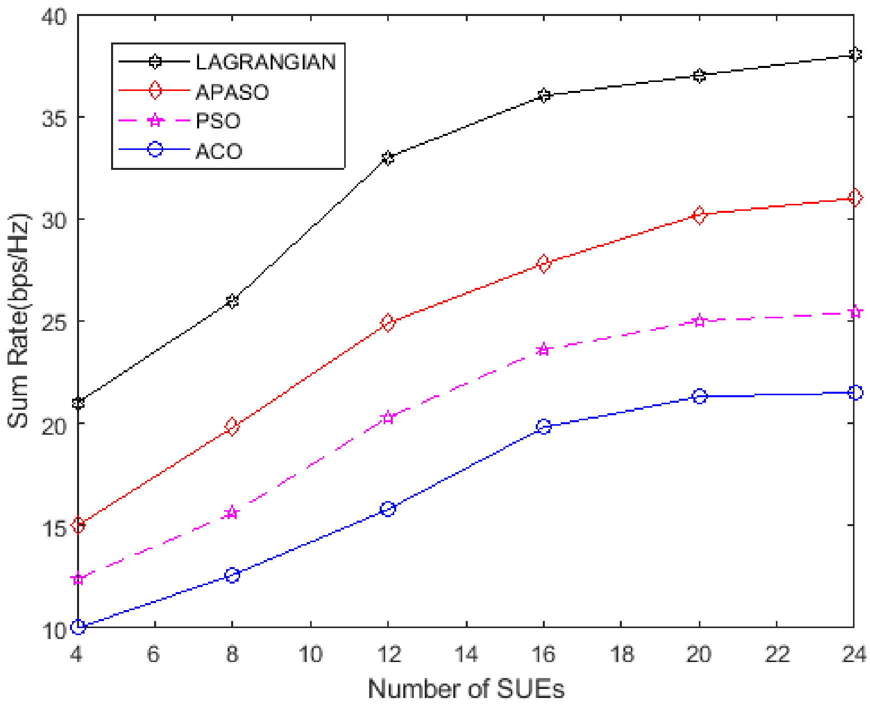

Fig. B.3: Sum-rate vs Number of users

Figure B.4 illustrates the variation of the sum-rate of the system vs total transmit power of users. As the transmit power is increased the sum-rate of the system increases until a saturation point is reached beyond which further transmit power increases do not yield increased sum-rate capacity of the system. The developed APASO outperforms the other biological algorithms, with the Lagrangian providing an upper bound.

The performance of the Lagrangian in figures B.3 and B.4 is similar to that demonstrated in [33].

In figure B.5, it is noted that as the number of users increases the energy efficiency of the systems decreases. Although the EE is higher in the beginning, it starts deteriorating with additional users in the system indicating that after the system has reached saturation, increasing number of users compromises the performance of the system. The performance of the algorithms follows a similar trend from Lagrangian to ACO.

In figure B.6, the EE of the algorithms is recorded as they are executed. The developed APASO

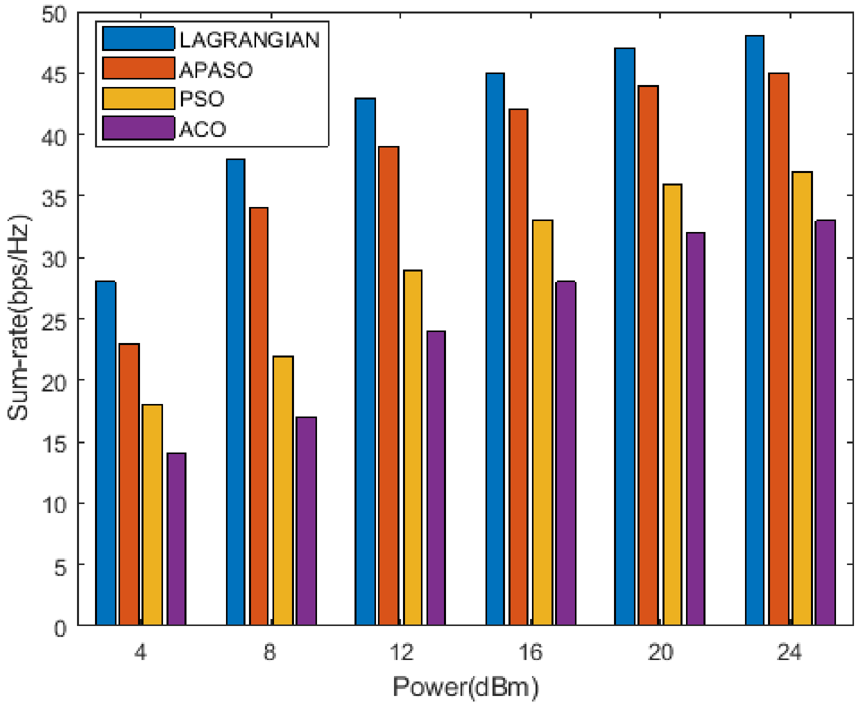

Fig. B.4: Sum-rate vs Total Power

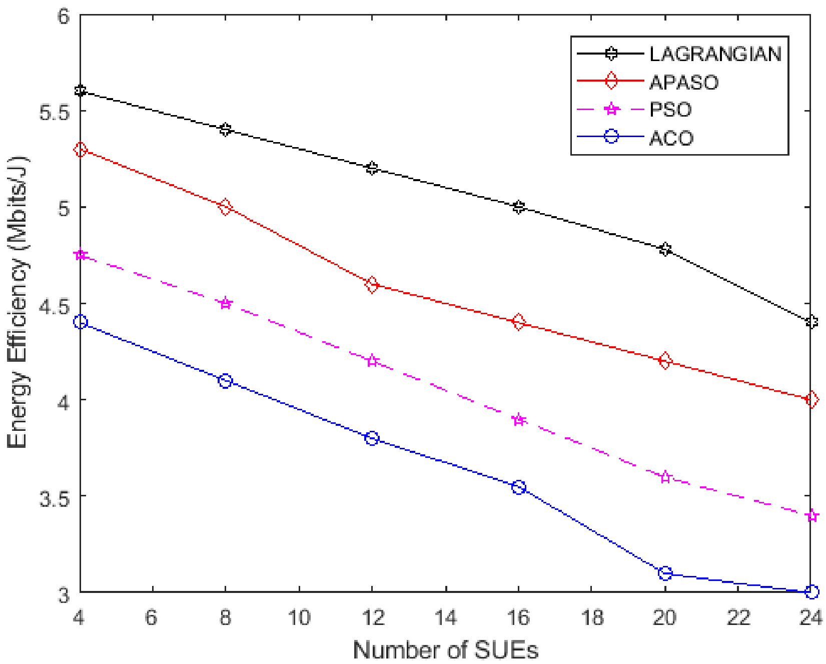

Fig. B.5: Energy efficiency vs Number of iterations

achieves higher EE and saturates faster than the other conventional biological algorithms. The pheromone mechanism adopted in APASO enhances its ability to find higher fitness ant particle solutions with higher EE. To evaluate the fairness of the algorithms in distributing resources among

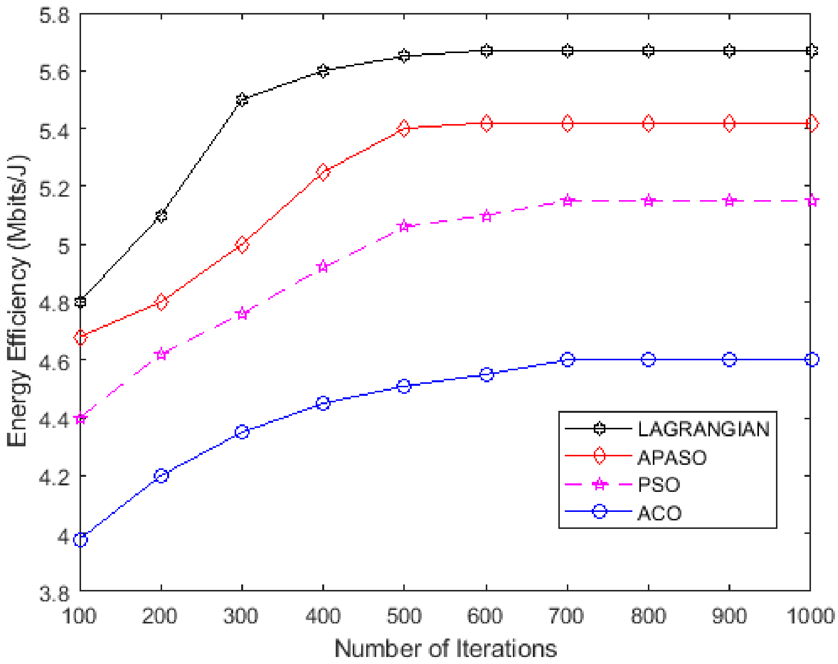

Fig. B.6: Energy efficiency vs Number of iterations

users in the network, Jain's fairness metric is embraced. It is defined as in [32] which can be expressed as

$$J = \frac{\left(\sum_{k=1}^{K} R_{k,n}^{FUE,i}\right)^2}{K \times \sum_{k=1}^{K} (R_{k,n}^{FUE,i})^2}. \tag{B.50}$$

In equation (B.50), the index has a range of $1/J$ (no fairness) to 1 (perfect fairness). In Figure B.7, the fairness performance of the considered algorithms is outlined. The ACO is observed to outperform other algorithms in terms of fairness as it has higher fairness index overall. This implies that the 'colony' of solutions derived using pheromone mechanism enables it to share resources more fairly among users albeit at the expense of maximizing the sum-rate. Its performance is followed by PSO and APASO with lagrange showing the worst performance. This implies that though the lagrangian algorithm provides better performance in terms of sum rate and energy efficiency, its the least fair.

A comparison of PD-NOMA, SCMA and PD-SCMA RA with application of APASO was investigated and the results of Figures B.8 to B.10 developed. In Figure B.8 the system sum rate versus total number of users is plotted. As it can be observed, the hybrid PD-SCMA has significantly higher sum rate than the other NOMA techniques. Figure B.9 shows the system sum rate versus total transmit power for the three MA schemes. The hybrid PD-SCMA outperforms the two conventional NOMA

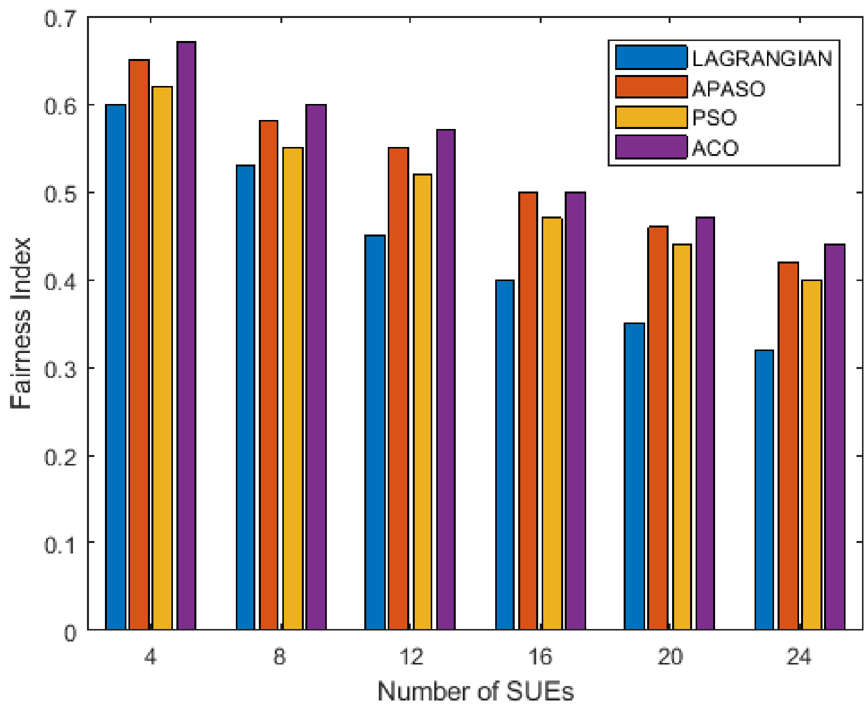

Fig. B.7: Fairness vs Number of users

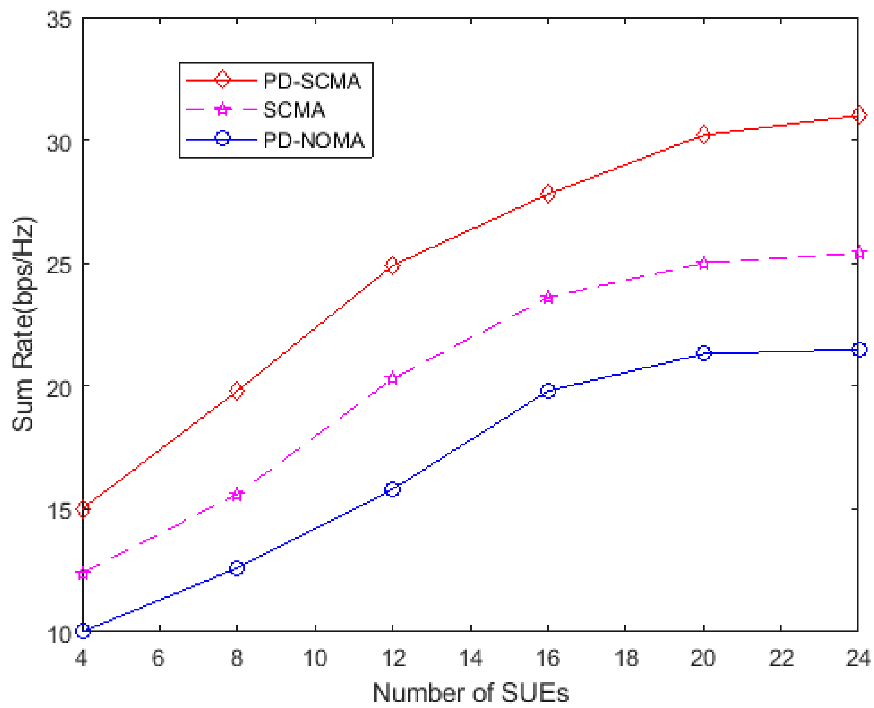

Fig. B.8: Sum-rate vs Number of users for different MA schemes using APASO

methods. A comparison of the energy efficiency of the three considered MA schemes against the number of iterations is displayed in Figure B.10. PD-SCMA is seen to perform better than the other

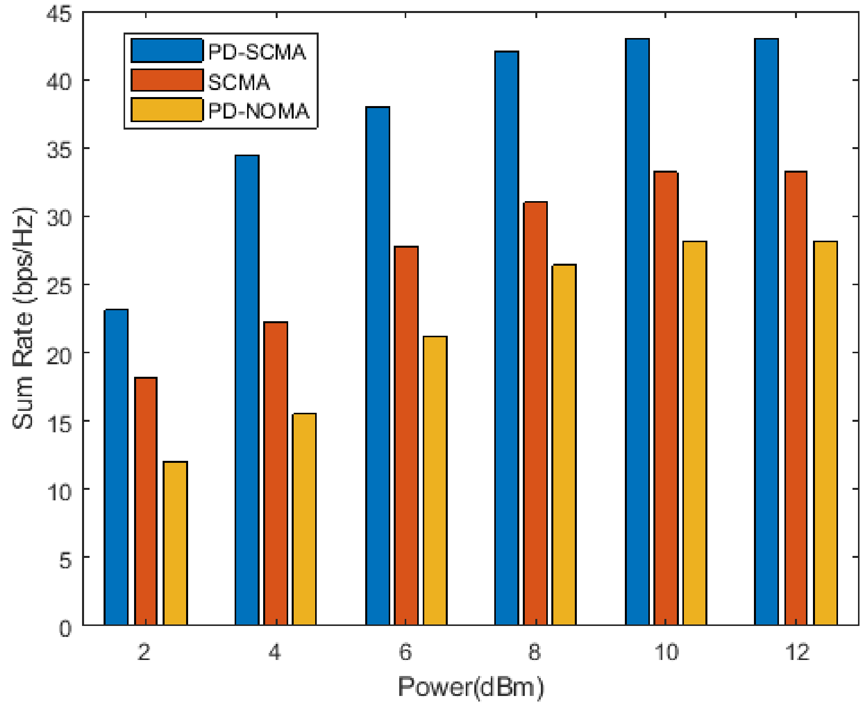

Fig. B.9: Sum rate vs total transmit power using APASO for different MA schemes

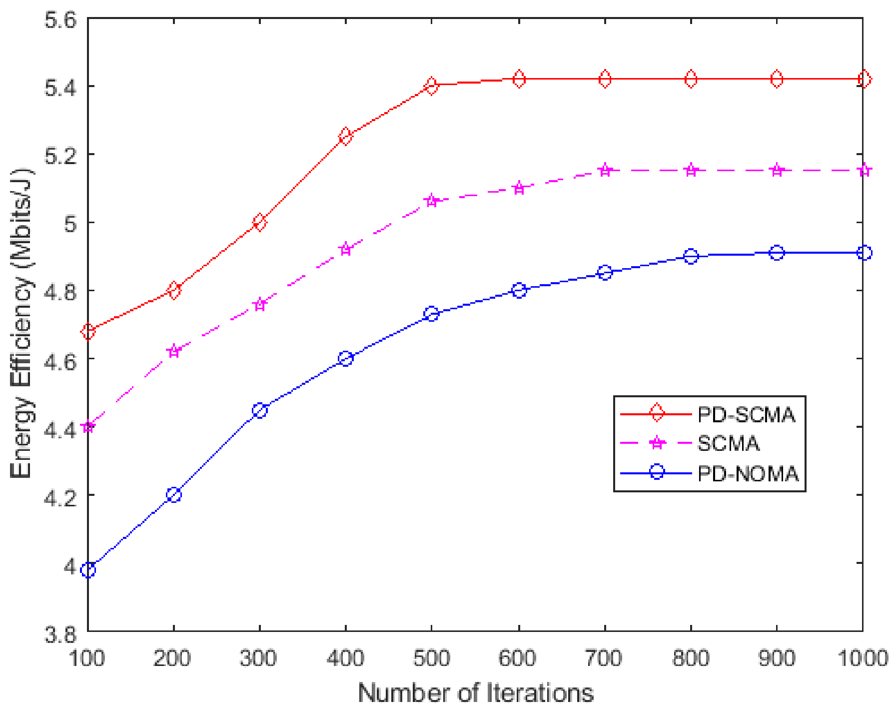

Fig. B.10: Energy efficiency vs Number of iterations for different MA schemes using APASO

two traditional NOMA approaches. The enhanced performance of PD-SCMA as compared to the conventional NOMA MA schemes can be attributed to the ability of PD-SCMA to merge access features of PD-NOMA and SCMA.

9 Conclusion

In this paper, the performance of nature-inspired algorithms, PSO, ACO and the developed hybrid APASO is investigated regarding sum-rate maximization, energy efficiency and fairness in a hybrid power domain SCMA setup. The investigative results show that the performance of APASO is better than the conventional biological algorithms (PSO and ACO) with respect to sum-rate and energy efficiency. However, ACO is observed to have a higher fairness index than the other considered algorithms. The developed results also show that the common Lagrangian based optimization can lead to system performance overestimation. PD-SCMA is observed to outperform the other considered traditional MA schemes when only APASO is employed for RA. Future work will consider more evolved hybrids with other advanced variants of biological algorithms that have been proven to be efficient in solving NP-hard problems. Furthermore, the performance of succeeding models should feature extended aspects like signaling overhead, channel uncertainty and many others for conclusive deductions.

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Part III

Conclusion

Conclusion

To conclude this thesis we will consider a summary of research contributions accomplished in this work and propose potential future research objectives that can be pursued in relation to this study.

In the introduction a detailed account of the evolution of wireless communication networks (including 4G and 5G networks) was presented. Research motivation, methodology as well as contributions were also lucidly expressed in the introduction. Notwithstanding their advantages of higher data rates, 4G/5G networks experience challenges of interference management and EE due to HetNet deployments aimed at maximizing overall system capacity. Resource allocation regarding finite resources such as spectrum and energy is thus crucial in optimizing the performance of these networks. This necessitates continuous efforts to investigate intelligent solutions as alternatives for already established analytical methods. This work developed architectural network models for multi-tier heterogeneous 4G LTE-A and 5G NOMA networks on the uplink. Metaheuristic approaches namely particle swarm optimization (PSO) and ant colony optimization (ACO) and the developed adaptive particle ant swarm optimization (APASO) were used for the RA of the new models. The performance analysis results show improved performance in terms of throughput, transmit power sum rate and energy efficiency.

1 Summary of research contribution

In paper A, RB allocation in SC-FDMA using meta-heuristic algorithms as alternatives to the conventional methods that are usually employed to solve the NP-hard non-convex problem that arises was considered. A hybrid particle swarm ant colony optimization methodology to embrace desirable traits of traditional PSO and ACO algorithms. Simulation results reveal that the hybrid APASO is able to attain better throughput as the number of UEs in the network increases than PSO and ACO. APASO reaches saturation faster than traditional algorithms and hence lower running time. Although, the ACO achieved better fairness in distributing resources than other methods, the proposed hybrid APASO had better energy efficiency performance than the other considered metaheuristic algorithms. The developed APASO has improved convergence compared to PSO and ACO. The performance of the metaheuristic algorithms is comparable to the approximate Lagrange technique that provides an upper performance bound.

In paper B, the performance of nature-inspired algorithms, PSO, ACO and the developed hybrid APASO is investigated regarding sum-rate maximization, energy efficiency and fairness in a hybrid power domain SCMA setup. The investigative results show that the performance of APASO is better than the conventional biological algorithms (PSO and ACO) with respect to sum-rate and energy efficiency. However, ACO is observed to have a higher fairness index than the other considered algorithms. The developed results also show that the common Lagrangian based optimization can lead to system performance overestimation. PD-SCMA is observed to outperform the other considered traditional MA schemes when only APASO is employed for RA.

2 Future Work

Future work will consider more evolved hybrids with other advanced variants of biological algorithms that have been proven to be efficient in solving NP-hard problems. Furthermore, the performance of succeeding models should feature extended aspects like signaling overhead, channel uncertainty and many others for conclusive deductions. The algorithms will then be evaluated from the computation model structures point of view. Descriptive statistical approaches would be valuable in analysing biological algorithm performance in future work.