Cost Efficient 5G Heterogeneous Base Station Deployment Using Meta-heuristics

By

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Abstract

Over the last two decades, the telecommunication industry has witnessed sustained growth in the number of mobile user devices driven by the introduction of data services, the take-off of the internet and smart user equipment. This growth, which is forecasted to continue, has continued to push the data transfer capacity requirement on mobile networks and has motivated research into the design of 5th generation (5G) mobile networks. A key concern in the design of 5G is the infrastructure and power consumption cost of the base station network which is expected to be significantly more advanced and dense than that of existing conventional mobile networks. This thesis presents an optimisation framework for the cost efficient design of 5G base station networks, based on the application of meta-heuristic algorithms.

The presented optimisation framework is centred on the ability to *exploit* three key technologies of 5G, a heterogonous base station network with small-cells, multi-antenna spatial multiplexing MIMO and cell range extension. The framework includes mathematical integer programming models for supporting the decisions about the optimal base station topology in a 5G mobile network and provides a clear core for the application of meta-heuristics for optimising 5G base station deployment. The core optimisation framework includes the definition of solution encoding/decoding and fitness mechanisms. To increase power consumption awareness of base station network design, an independent base station deployment strategy has been presented and evaluated. Simulation results show that the strategy can improve base station network design power consumption by as much as 34%.

The work in this thesis has been extensively evaluated using a simulated 5G mobile network system model. Evaluations of algorithms have been performed through empirical

measurements. The main contribution of this thesis is the definition of a clear framework for application fitness based heuristic search in the design of 5G mobile networks.

Contents

The following key notations are used throughout this thesis.

General

RAN	Radio access network
nG	nth generation
BS	Base station
BSs	Base stations
UE	user equipment/terminal
QoS	Quality of service
LTE-A	Long term evolution (Advanced)
MNO	Mobile network operator/owner
RF	Radio frequency
MIMO	Multiple Input Multiple Output
CRE	Cell range extension technology
CAPEX	Infrastructural Expenditure
OPEX	Operational Expenditure
TCO	Total cost of ownership
HetNet	Heterogeneous base station access network

Mathematical

$\boldsymbol{x}$	Matrix or vector
x_{ij}	Matrix element at row i column j
X	Set
$\lvert X \rvert$	Cardinality of set X
$x \in X$	x is an element of X
$X_1 \cup X_2$	The union of sets X_2 and X_1
$X(i)$	ith element of X

Algorithms

SA	Simulated Annealing Algorithm
Λ	Simulated Annealing cooling rate
GA	Genetic Algorithm
HC	Hill Climbing Algorithm
RSM	Random sampling approach

Other notations are defined in the respective chapters.

“All models are wrong, but some are useful”

George E. P. Box

ACKNOWLEDGEMENTS

I want to especially thank my principal supervisor, **Prof. John Cosmas** for his encouragement and guidance towards completing this thesis. I would also like to express my deep gratitude to **Dr Stephen Swift** for his very generous support. I definitely would not have completed this thesis without their experience and guidance. I would also like to thank my father **Chief Micheal Kaase Aondoakaa SAN** and my family for their support throughout my PhD research. Finally, I would like to thank my second supervisor, **Prof. Hamed Al-Raweshidy** who provided some valuable feedback on my research.

DECLARATION

I declare that this thesis is my own work and is submitted for the first time to the Post-Graduate Research Office. The study was originated, composed and reviewed by myself and my supervisors in the Department of Electronic and Computer Engineering, College of Engineering, Design and Physical Sciences, Brunel University London UK. All the information derived from other works has been properly referenced and acknowledged.

SIGNED: .... DATE: ....

1. Introduction

Cellular mobile communication systems have evolved over the last two decades into the landmark technology for providing ubiquitous wide area wireless communication services to the population in any civilised society, with fourth-generation (4G) LTE-Advanced representing the state of the art. Different from the earliest cellular system standards, current cellular systems are data traffic oriented as opposed to voice. The introduction of third-generation (3G) mobile networks and smart user equipment in the mid-2000s instigated an exponential trend in the number of mobile subscribers and the demand for mobile data traffic, with the volume of mobile data traffic carried by mobile networks exceeding voice traffic for the first time in 2010 [1]. This exponential growth in the demand for mobile data services which began with the introduction of 3G mobile systems is expected to continue for the foreseeable future [2]. The 2017 Cisco visual networking index [2] reported that global mobile data traffic will increase sevenfold between 2016 and 2021. Mobile data traffic will grow at a compound annual growth rate of 47% from 2016 to 2021, reaching 49.0 Exabyte per month by 2021. This aggressive growth and projections are mainly due to the proliferation of smart user equipment and the rapid penetration of mobile services in developing societies. Cisco predicts there will be 11.6 billion mobile-connected devices by 2021, including machine to machine (M2M) nodes; far exceeding the world's human population projection at that time (7.8 billion people [3]). Globally, 74.7% of mobile devices will be smart devices by 2021, up from 36.7% in 2016. The vast majority of mobile data traffic (98 %) will originate from these smart devices by 2021, up from 89% in 2016.

In response, and in a competitive market, mobile network stakeholders have continued to seek strategies to provide higher data handling capacity into their networks in order to maintain and grow their market share. In fact, this trend has motivated research into the modelling, design and operation of future fifth generation (5G) mobile networks [4][5][6]. 5G mobile networks are to be designed with the main objective of providing *very high* levels of data speed for subscribers in all scenarios, by leveraging many advanced technologies and very dense deployment of base stations as a key feature, since current mobile networks based on LTE 4G standard have almost approached fundamental limits of spectral link efficiency [7]. One of such advanced technologies is the transition from a *flat homogenous* base station access network architecture to a dense *multi-tier heterogeneous* base station access network with *small-cell* base stations. A multi-tier heterogeneous base station access network deviates from traditional flat homogenous base station access network by the introduction of *local* base stations knows as *small-cells*. Other technologies include the use of aggressive multi-antenna spatial multiplexing (known as MIMO), millimetre wave spectrum, on-demand network optimisation etc.

1.1. Motivation

A key challenge of implementing next-generation 5G mobile networks is the effect of the base station access network on the system cost [8][9]. The dense deployment of base stations is poised to drastically increase the system deployment cost and power usage of mobile networks. The base station network accounts for over 80% of the power usage in a typical mobile network, in addition to expensive site acquisition and equipment cost, with energy bills representing up to 15% in mature markets and 50% of the network operational cost in developing markets with a high number of off-grid sites [10]. The high power consumption of telecommunication networks also contributes to an increase in (carbon dioxide) CO_2 emission in the environment [11]. Generally, increasing the base station network density and complexity increases traffic handling capacity of the network; however, this also leads to an increase in the capital and operational expenditure incurred. Consequently, mobile network operators are faced with a question concerning this trade-off, of *how to meet the very high* *system capacity requirement of next-generation 5G mobile networks at reduced system cost; which will be largely contributed by the base station deployment*? To compound this challenge, mobile network operators have been reporting flat revenues; however, users are expecting higher and higher data speeds but are unwilling to pay more [12].

1.2. Research Scope and Aim

Research into strategies for minimising the cost implications of the base station network is required in the build-up to 5G mobile networks. Such strategies are expected to minimise system cost without compromising the required capacity and coverage metrics seen by subscribers. One direction is focusing on cost and power consumption *modelling* of different base station network architectures. These models are important for gaining insights into the cost implications of different network designs in different scenarios. The other direction is focusing on techniques for maximising network cost efficiency. Given that the base stations consume the most power in a mobile network system, improving the power efficiency of the base stations at the component level is an active research area. For example, [13] discussed a conceptual strategy for improving the base station power amplifier efficiency, since the power amplifier consumes the most power relative to all other components. Beyond base station component level improvements, research into powering cellular access networks with renewable energy has also received increased attention. For example, authors in [14] proposed an optimisation framework for dimensioning photovoltaic power generators and energy storage to power the base station access network. At the link level, quite a number of improvements of radio interfaces have been achieved in the last decade, boosting spectral power efficiency i.e. the number of data bits that can be transferred for a fixed amount of spectrum and power. However, current state-of-the-art 4G LTE mobile systems based on orthogonal frequency division multiple access (OFDMA) are approaching fundamental link efficiency limits through the use of higher order modulation schemes [7].

In practice, the cost efficiency gains of component and link level strategies in base stations are limited, and the main gains are expected at the network level in the topology layout of base stations [13]. A key network level strategy for minimising power consumption that has gained research momentum in recent years is the *management* of base stations on-demand. Base station networks are usually planned based on peak traffic hours which can be as high as 10 times the off-peak hours, however, currently base stations have limited ability to significantly scale their power consumption with traffic load; leading to very poor power efficiency in off-peak hours [15]. Spatial user traffic demand variation may also lead to poor network performance. To address this problems, the base station network should be *managed* such that unneeded base stations can be switched to *sleep* mode, while the configuration of the remaining network is adjusted to provide the required quality of service [16]. In this context, *heuristic algorithms* that can decide the topology of the network on demand in a power efficient manner have been a key research objective. The above approaches mainly focus on minimising the power consumption of the network and do not address the huge capital expenditure that will arise from the dense deployment of base stations in 5G. A more proactive approach is to *design*/*plan* a base station network that minimises the cost of the base stations deployed in the first place which includes both the infrastructure as well as the power consumption costs. *Base station planning* has been a fundamental research area in mobile networks where the main objective is to design a base station topology that minimises system cost without compromising the experienced subscriber quality of service measured by network coverage and capacity. However, the design of a mobile network is a complex task involving many variables and has since motivated the development of optimised design support tools. In general, the design process is facilitated by mathematical models and heuristic algorithms for supporting the decisions on where to install new base stations and the selection of their optimum configurations so as to find an optimal trade-off between system performance and minimising system cost. The use of heuristics is necessary because of the complexity and difficulty of solving these mathematical models at scale using exact methods. The literature abounds with mathematical models and study of heuristics, particularly meta-heuristics, for planning traditional mobile base station networks typical of 2nd and 3rd generation cellular standards. These models which are based on the assumption of a *flat*, *sparse* and *homogenous* base station network architecture typical of early cellular networks, are not optimised for planning of current 4G and next-generation 5G mobile networks which are based on a *multi-tier heterogeneous base station network architecture* incorporating advanced technologies like massive antenna *spatial multiplexing* MIMO and *cell range extension*. Furthermore, 5G mobile networks are expected to consist of significantly denser deployment of base stations (than current mobile networks) in order to provide high levels of data transfer capacity. This motivates the development/study of advanced and novel base station network planning models and heuristics for 5G mobile networks if mobile networks operators are to maximise the cost efficiency of 5G, and is indeed the main focus of this thesis. The research scope of this thesis is illustrated in Figure 1.1.

The aim of this thesis is to develop and study a base station planning scheme for **'cost efficient'** topology design of next-generation 5G base station access network architecture based on the application heuristic search optimisation. To achieve this aim, the following contributions have been made:

1. The proposal of integer programming models for supporting the decisions on the deployment of an optimal base station topology in a 5G mobile network so as to find a trade-off between providing '*high capacity everywhere*' requirement of 5G and minimising system cost. The proposed network design integer programming models are based on the hypothesis that operators can *jointly exploit* configuration *heterogeneity* offered by heterogeneous base station network architecture (with

different classes of base stations) and advanced technologies such as MIMO and cell range extension to deploy a high capacity network that minimises cost both in terms of infrastructure (CAPEX) and power consumption.

2. The second contribution is the definition of a clear framework for the application of iterative fitness based heuristic search techniques such as *meta-heuristic* for planning 5G mobile networks. The framework includes a solution encoding, fitness function and definition of search operators. Using the framework, the performance of three heuristic search techniques, namely; Genetic algorithm, Simulated annealing and Hill climbing are analysed as deployment algorithms for 5G.

3. Thirdly, an independent power consumption aware strategy for planning 5G base station networks, based on the principle of *divide and conquer co-operative optimisation* is proposed. Empirical simulation results validate that the proposed base station planning strategy is able to save as much as 34% of overall network power consumption depending on the traffic demand scenario.

The contributions made in this thesis have been published/presented in:

- Aondoakaa, D., Cosmas, J. and Swift, S. (2018) '**Exploiting Heterogeneity For Cost Efficient Cellular Base Station Deployment Using Metaheuristics**', in *482nd International Conference on Communication and Signal Processing* (ICCSP). Dubai, UAE. [Awarded Best Paper certificate]

- Aondoakaa, D., Cosmas, J. and Swift, S. (2018) '**Exploiting Heterogeneity For Cost Efficient Cellular Base Station Deployment Using Metaheuristics'**, *International Journal of Advances in Electronics and Computer Sciences* (IJAES), 5(10).

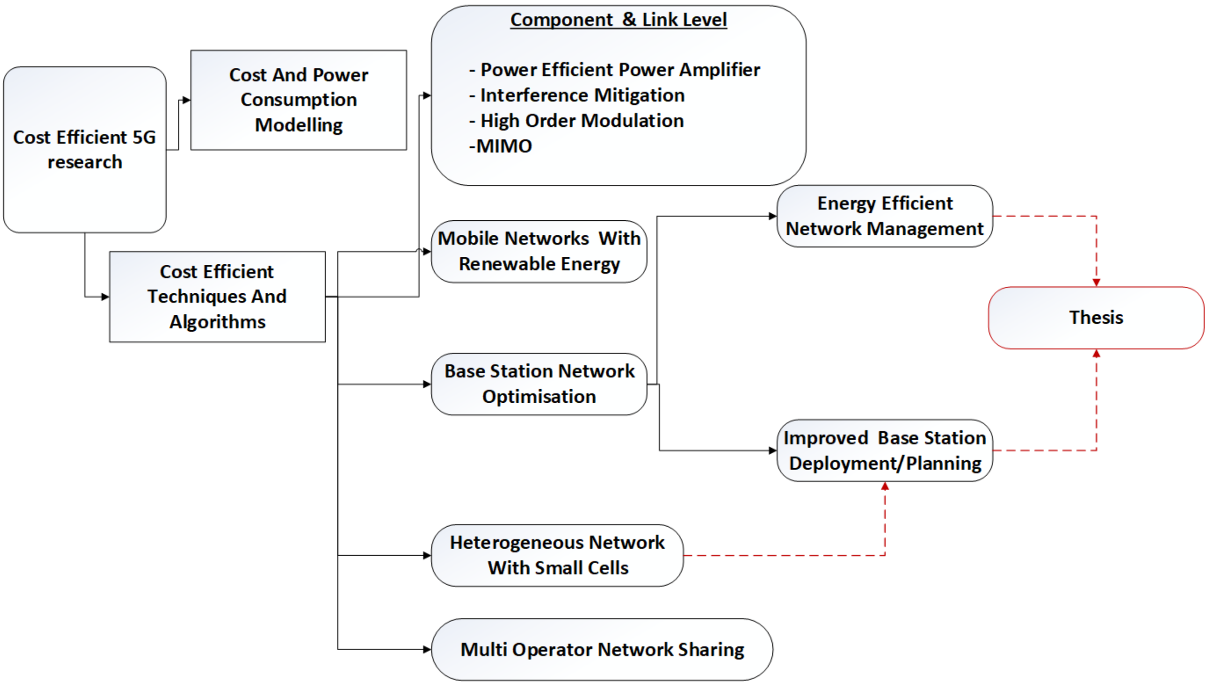

Figure 1.1: Diagram showing research scope

1.1. Thesis Outline

This thesis is organised as follows:

Chapter 2 provides background knowledge on the main concepts, techniques and methods that are used in this thesis. It starts with an overview of the fundamentals of mobile cellular networks and their evolution towards next-generation 5G mobile networks. Next, key technologies for 5G mobile networks that include a Heterogeneous access network, small-cells, and MIMO are reviewed. Finally, an overview of optimisation is presented and the meta-heuristic techniques which have been utilised for this research are described.

Chapter 3 presents a literature review on cellular base station network optimisation with emphasis on problem modelling and the use of meta-heuristics and the transition to 5G heterogeneous base station mobile network architecture. The chapter characterises research development over time, analyses the state of the art and positions the contributions made in this thesis. This chapter also includes the definition of key terms.

Chapter 4 describes the system model used for deployment analysis of a 5G mobile network with heterogeneous base stations based on the 4G LTE-Advanced cellular downlink standard. The system model described is based on mathematical representation and is derived by *unifying* existing models from the literature. The described model explicitly relates cost and quality of service (QoS) performance modelling of a base station access network as a function of the base station deployment and forms the basis for all the conclusions reached in this thesis. That is, for a given base station topology, the system model returns the system cost and performance implications with respect to the traffic scenario.

Chapter 5 first presents an optimisation framework for the application of iterative fitness based heuristic search to the deployment of 5G heterogeneous base station architecture with cell range extension technology. The framework which is generic to both greenfield and expansion base station planning has three components: an integer programming 5G Heterogeneous base station deployment solution, which is engineered towards exploiting base station heterogeneity for cost efficient base station deployment; a solution encoding, and a fitness function. Next, the performance of three meta-heuristics algorithms; Simulated annealing, Hill climbing and Genetic algorithm are analysed as base station deployment tools for 5G.

Chapter 6 proposes and evaluates a power-aware 2-Phase incremental strategy for the 5G base station deployment challenge formulated in **chapter 5** that is independent of the meta-heuristic algorithm used as the optimisation tool. The strategy is evaluated by comparing the average fitness and the network cost of the returned network topology when the strategy is used, against when it is not.

Chapter 7 extends the 5G deployment challenge in **chapter 5**, to propose and analyse the benefit an *advanced* 5G base station deployment problem model that jointly optimises heterogeneous base station types, MIMO and Cell range extension configurations for achieving cost efficient and high capacity base station deployment. The *advanced* 5G base station deployment problem model is evaluated by comparing its cost efficiency against existing models in the literature.

Chapter 8 summarises the whole thesis. This chapter examines what has been developed within this research project and how this can be extended as further work.

2. Background Information

This chapter provides background knowledge key to the work presented in this thesis. It starts with an overview of the fundamentals of mobile cellular networks and their evolution towards next-generation 5G mobile networks. Key technologies for 5G mobile networks that include a Heterogeneous base station access network, small-cells, and MIMO are overviewed. Finally, an overview of optimisation is presented and the meta-heuristic techniques which have been utilised for this research are described.

2.1. Cellular networks: The Basics

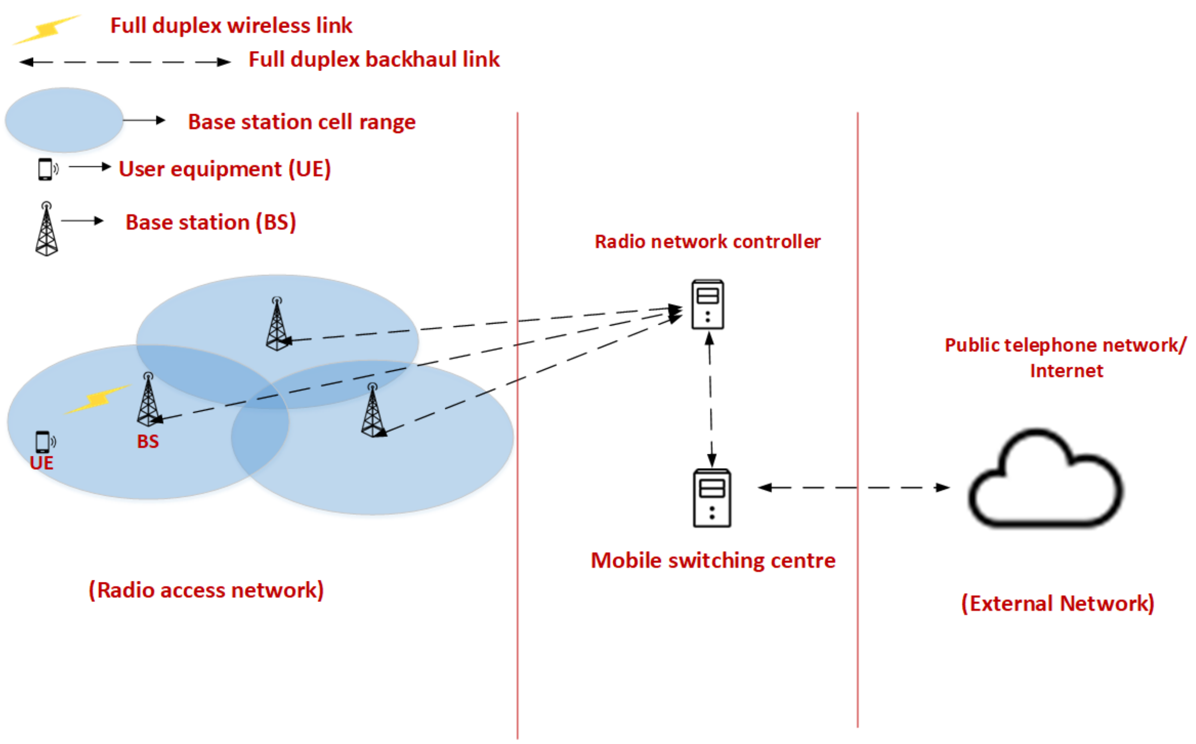

Figure 2.1: Typical cellular mobile network architecture

A mobile cellular network (MCN) is a communication network designed to provide wide area wireless communication services. A typical MCN consists of two parts; a radio access network (RAN) and a backhaul network that connects the RAN to the external network (Figure 2.1). The RAN, which is the focus of this thesis, consists of a collection of transceivers, called Base Stations (BSs) that transmit/receive information in the form of wireless signals to/from subscribers with user equipment (UE). Each base station (BS) provides radio coverage to a small geographical area, known as its *cell*. The integration of the coverage of various BSs provides radio coverage over a much larger geographical area, thus defining a mobile cellular network. Cellular network base stations communicate with subscribers through a government licenced radio frequency (RF) band based on a physical layer air interface. Communication from the base station to the user equipment is known as the *downlink*, while communication from the user equipment to the base station is *uplink*.

2.1.1. Mobile networks: Evolution towards 5G

The first-generation (1G) of mobile telecommunication systems was released in Europe in the early 1980s. 1G mobile network standard was based on analogue communication techniques and extremely large cell size base stations, in order to provide large network coverage footprints. The 1G user equipment was bulky and expensive and were mainly limited to high profile and government users [17]. The launch of the second-generation (2G) Global System for Mobile Communications (GSM) by the European Telecommunications Standards Institute (ETSI) really kick-started the revolution of mobile networks as a landmark wide area wireless communication system and also the need for its proper planning. 2G networks were developed as a replacement for the first-generation (1G) analogue mobile networks, and the GSM standard was originally described as a digital, circuit-switched network, optimised for full duplex voice telephony, which enhanced the efficiency of the radio spectrum usage, and led to the introduction of smaller and less expensive mobile phones. GSM was expanded over time to include data communications, first by supporting instant messaging service (SMS) and circuit switched data services up to 9.6Kbps data rates. Packet switching data capabilities were added to GSM using general packet radio services (GPRS), known as 2.5G. The 2.5G systems had a maximum theoretical downlink rate of

171Kbps which was further improved to reach 384Kbps through enhanced data rates for GSM evolution (EDGE). As a result, the data usage increased, but the traffic volume in second-generation networks remained dominated by voice traffic. The need to support faster data rate services motivated the evolution to the third generation 3G cellular system standard. The Third-Generation Partnership Project (3GPP) was formed to develop the 3G Wideband Code Division Multiple Access (WCDMA) and Time Division Synchronous Code Division Multiple Access (TD-SCDMA) technologies. The Universal Mobile Telecommunication System (UMTS) was proposed as an evolution to GSM and quickly became the world's dominant 3G system [17]. It initially had a downlink typical user data rate of 384Kbps to 2Mbps, which was later enhanced to 10Mbit/s with the 3.5G technologies of high-speed downlink packet access (HSDPA) and high-speed uplink packet access (HSUPA). Architecturally, 3G cellular systems employed base stations with smaller cell sizes than GSM and were based on single frequency reuse among all the cells. The third evolution of cellular systems also happened on the user equipment side, as '*smarter*' user terminals were developed to take advantage of the increased data transfer rates of the system. The 3G era really introduced various value-added services like video calling, live streaming, mobile internet access, IPTV etc. on mobile phones. These services were possible because the 3G standard provided the basic data speeds they required.

2.1.2. LTE 4G and beyond

The popularity of smart user equipment running fun and social applications such as high definition (HD) video and audio streaming, online gaming etc. motivated another evolution to the current state of art cellular mobile system, fourth-generation Long Term Evolution (LTE) in order to provide more data handling capacity than previous 2G and 3G systems which had become congested and unable to meet the continuous growth in data demand. LTE cellular standard was developed by 3GPP as a high-speed data-oriented standard based on packet switching technology with the following basic target performance (relative to 3G HSPA) [18]:

- Two to four times spectral efficiency compared with the HSPA Release 6.
- Theoretical peak rates of more than 100Mbps downlink and 50Mbps uplink.
- High level of mobility and security.
- Optimised terminal power efficiency.
- Flexibility in frequency allocation from below 1.5 MHz up to 20 MHz.

The LTE mobile network standard is based on Orthogonal Frequency Division Multiple Access (OFDMA) in the downlink and Single Carrier Frequency Division Multiple Access (SC-FDMA) for the uplink. The LTE standard was first launched in 2009 as release 8 and has witnessed a number of enhancements in subsequent releases aimed at providing even higher data capacity. The LTE standard comprises of many advanced technologies and features that were not supported or matured in earlier generation mobile systems;

- All IP network.
- Support for 8x8 MIMO in downlink and 4x4 in the uplink.
- Support FDD and TDD duplex mode.
- Support for heterogeneous access networks and femto-cell base stations
- Co-operative multipoint transmission and reception (CoMP).
- Carrier aggregation.
- Self-organising functionality (SON) improvement.
- Support for relay base stations etc.

Exponential growth in the demand for mobile data services which began with the introduction of 3G mobile systems is expected to continue for the foreseeable future [2]. The 2017 Cisco visual networking index [2] reported that global mobile data traffic will increase sevenfold between 2016 and 2021. Mobile data traffic will grow at a compound annual growth rate of 47% from 2016 to 2021, reaching 49.0 Exabyte per month by 2021. This aggressive growth and projections are mainly due to the proliferation of smart user equipment and the rapid penetration of mobile services in developing societies. Cisco predicts there will be 11.6 billion mobile-connected devices by 2021, including M2M modules; exceeding the world's projected human population at that time (7.8 billion [3]). Globally, 74.7% of mobile devices will be smart devices by 2021, up from 36.7% in 2016. The vast majority of mobile data traffic (98%) will originate from these smart devices by 2021, up from 89% in 2016. In response, mobile network stakeholders have encouraged research into the standardisation and release of fifth-generation (5G) of mobile networks. The 5G cellular network is expected to inherit all of the features of 4G LTE standard as well as introduce new technologies and strategies in order to provide very high mobile data capacity. Design requirements for 5G include a minimum downlink average user throughput of 50Mbps '*everywhere*' and up to 1Gbps in ideal scenarios[19][20]!

The following technologies are considered key to achieving 5G high capacity requirement:

2.1.3. Heterogeneous networks (HetNet)

In traditional mobile network architecture, a cellular base station was designed to provide wireless service over a sizeable area enabled by its high power consumption signal amplifier [21]. This type of base station is known as a *macro* base station and was deployed homogenously in 1st, 2nd and 3rd generation cellular systems. A GSM macro base station provides signal up to 10km in rural areas [22]. Due to their large coverage footprints, relatively few macro base station sites were required to provide signal coverage over an area. Driven by an aggressive increase in data traffic demand over the last decade, successive cellular system standards have however seen reductions in cell sizes of macro base stations resulting in denser base station deployments, providing higher system capacity, especially in urban centres. However, their site acquisition costs in a capacity limited dense urban area can get prohibitively expensive as well as the increasing power consumption cost of operating them [7]. LTE 4G cellular standard formally introduced the concept of a *heterogonous base station access network* (HetNet) as cost effective solution to macro base station densification. A Heterogeneous base station network is considered a key architecture for next-generation 5G cellular systems and is a paradigm shift from macro base station only constructed cellular systems. The idea of a HetNet is to complement traditional long-range macro base stations with relatively small-cell base stations that have local range and low power consumption to extend coverage or boost system capacity. In traditional base station network architecture, the macro base stations are carefully placed to control the level of coverage overlap to minimise potential signal interference between base stations transmitting signals to different sets of users using the same frequency band. Controlling the overlap between base stations is also critical during network deployment to avoid base station redundancy leading to unnecessary system cost [23]. In contrast, in a HetNet, low range and power base stations can be deployed completely under the footprint of macro base stations using the same frequency band as a means of boosting coverage and capacity. Such a deployment scenario would require interference mitigation techniques to avoid potential high levels of signal interference between macro and small-cell base stations. One way to avoid inter-tier interference (i.e. interference from the macro base station to small-cell base station signal and vice versa) is to deploy small-cells on a different frequency band, however, this may reduce spectral efficiency.

2.1.3.1. Small-Cells

The LTE cellular standard defines different classes of small-cell base stations for different use cases. Aside from very low power consumption, due to their smaller physical size, small-cell base stations offer flexible site acquisition, which minimises infrastructure cost of the system. For example, small-cells can be easily deployed on street lamp posts [7].

However, although the grid power consumption contribution per small-cell base station is relatively lower (compared to traditional macro base stations), a dense deployment of these base stations that is expected in next-generation 5G cellular systems still raises sizable power consumption concerns, which form the bulk of operational cost for mobile network operators (MNO), as well as capital expenditures [10].

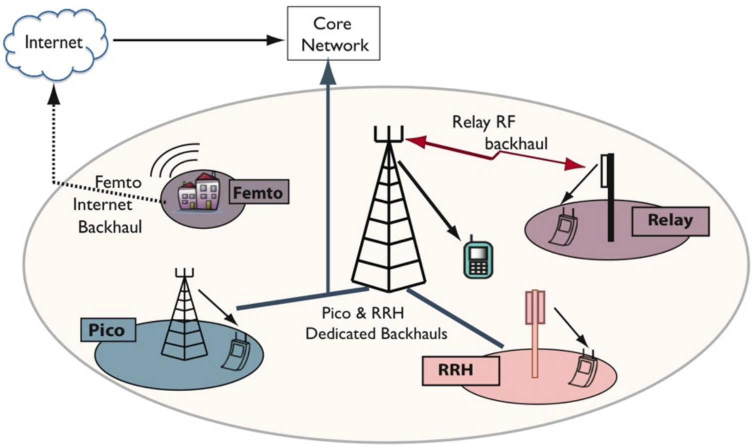

Figure 2.2: Heterogeneous base station access network consisting of different classes of base stations [24]

2.1.3.2. Micro / Pico and Relay Base stations

Micro/Pico/Relay small-cells are regular base stations with the only difference of having a smaller size, range and power consumption than traditional macro-cell base stations. They are typically equipped with omnidirectional antennas (as opposed to directional/sectored antennas) and are deployed and managed indoors or outdoors in a planned manner by mobile network providers using base station planning tools. Their transmit power ranges from 250mW to approximately 2W for outdoor deployments, while it is typically 100mW or less for indoor deployments [7]. These small-cells are deployed as part of the mobile network operator’s core base station infrastructure and benefit from tight cooperation with macro base stations especially for inter-cell interference coordination (ICIC). Relay small-cells are unique in that they do not have wired backhaul i.e. the backhaul link is wireless. The backhaul, which provides the attachment of the relay to the rest of the network, may or may not use the same air interface resources of the cellular system in question.

2.1.3.3. Femto Base stations

Femto small-cells are indoor base stations much like Wi-Fi access points. They are typically consumer deployed in an unplanned manner for improving indoor cellular coverage and are backhauled via an internet connection such as DSL or cable modem. Femto cells are typically equipped with omnidirectional antennas with maximum transmission power of about 100mW [25]. Similar to residential Wi-Fi network, femto-cells are owned and managed by users and usually operated in restricted access mode i.e. only registered user devices can connect to them.

2.1.3.4. Cell Range Expansion (CRE)

A key-enabling feature standardised by 3GPP for heterogeneous base station access network is the technology for small-cell range expansion/extension (CRE) [26]. As illustrated in Figure 2.3, to attract more users, small-cells enabled with the CRE feature use a positive cell selection offset on their pilot channels. The major benefit of CRE is to avoid low utilisation of small-cells and over congestion of macro-cells by active users (i.e. load balancing). User devices usually attempt to connect to the base station from which they measure the strongest pilot power. However, due to the transmit power disparity between macro and small-cell base stations, active users that could have connected to a nearby small-cell base station still connect to the high power macro base station. This creates a situation where macro base stations become overloaded while the small-cells are practically free of user demand. CRE solves this problem by applying a positive cell selection *bias* to the pilot power of small-cells to attract more users from the macro base station. Finding an optimal *bias* for each small-cell base station results in challenging optimisation task in itself [27].

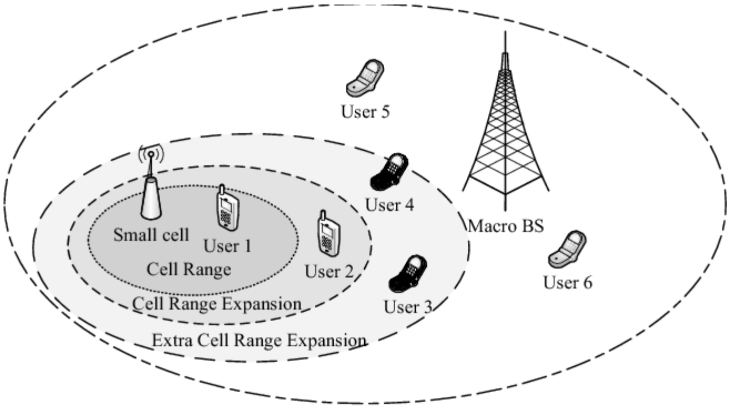

Figure 2.3: Illustration of small-cell range expansion in a heterogeneous network [28]

2.1.4. MIMO

(Multiple Input Multiple Output) MIMO is an advanced data transmission technique based on the concepts of *Spatial multiplexing* and *Transmitter diversity* [29]. A simple point to point MIMO enabled system consists of a base station and a user device with multiple antennas to transmit and receive data. Every use of the channel comprises transmitting a signal vector and receiving a signal vector, where every received signal is a linear combination of transmitted signals, and the combining coefficients are determined by the propagation between the two ends of the link (between the base station and the user). MIMO spatial multiplexing is a key technology used in LTE and key to next-generation 5G mobile networks [30]. MIMO *Spatial multiplexing* is used to increase the overall data rate through transmission of two (or more) different data streams on two (or more) different antennas, using the same resources in both frequency and time; separated only through the use of different reference signals, to be received by two or more antennas, see Figure 2.4. However, MIMO spatial multiplexing can only be efficiently used under a high-quality radio channel indicated by a high Signal to Noise ratio [29]. MIMO can also be used to improve the link quality by means of *Transmit diversity*. In this mode, all the antennas transmit the same data which is then combined by the receiving antennas to improve data decoding reliability. 5G mobile networks are expected to feature base stations with very aggressive MIMO orders [30][29].

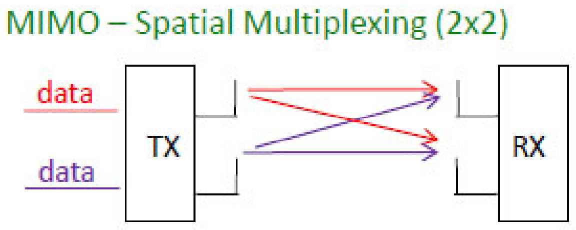

Figure 2.4: Simplified illustration of 2x2 MIMO (Spatial Multiplexing). Two different data streams are transmitted on two TX antennas and received by two RX antennas, using the same frequency and time, separated only by the use of different reference signals[31].

2.2. Optimisation

This sub-section provides *general* background knowledge on *optimisation* in sufficient detail for the reader to better appreciate the content of this thesis. A complete background on optimisation is out of scope and the reader is referred to [32]. Optimisation is a key decision-making tool which has been applied in diverse subject areas and indeed in mobile networks. Optimisation has historically played an important role in mobile networks and is poised to be central in the design and operation of next-generation 5G cellular networks, which are expected to be significantly more complex. Many complex decisions can be formulated as *optimisation models*/*problems* and analysed. A typical optimisation framework consists of two parts:

1. **Problem model and formulation**: A problem model is usually an abstract mathematical representation that captures the main characteristics of the problem to be optimised. Usually, models are intelligent simplifications of reality [33]. They involve approximations/assumptions and sometimes may skip processes that are complex to represent mathematically but can easily be modified and are still able to provide useful insights to the modelled problem. As part of the problem formulation, a set of *decision variables*, *objective*(s) and *constraints* that characterise the problem are clearly identified.

2. **Optimisation Method:** Once the optimisation problem is formulated, the next step is to solve the model, which involves finding the *optimal* values of the decision variable(s) to the model based on the objectives(s) and respecting the constraint(s) of the problem. Typically, efficient algorithms are developed to solve the model, either to optimality or approximately. More details on algorithms are given in subsequent sections.

An optimisation problem may be defined by the couple (S, f), where S represents the set of *feasible* solutions, and $f : S \rightarrow R$ the objective function to be optimised [32]. The objective function assigns a quantitative *fitness* value ($r \in R$) to every solution ($s \in S$) of the *search space*, indicating its quality at solving the model relative to any other solution in the *search space*. The solution $s \in S$ assigned the best fitness by the objective function out of the pool of all other feasible solutions to the problem is the *global optimum*. Optimisation problems may have more than one global optimum. In many complex optimisation problems such as mobile network design, finding the *global optimum,* is a near impossible task in acceptable computational time and a *good* approximation of the global optimum is sought instead.

Definition 2.1: *Feasible solution*. A candidate solution to an optimisation problem is *feasible* if it obeys the constraints to the problem.

Definition 2.2: *Search space*. The set of all possible solutions for any given optimisation problem. A search space will contain feasible and infeasible regions based on the constraints of the optimisation problem. The size of the search space is closely defined by the number/nature of decision variables to the problem.

Definition 2.3: *Global optimum*. A solution $s^* \in S$ is the global optimum if it has a better objective value than all solutions of the search space, i.e. $\forall s \in S, f(s^*) \leq f(s)$ for a minimisation problem.

Definition 2.4: *Local optimum*. A solution or point $s' \in S$ is a *local optimum* if it has a better objective function value than nearby points in the search space and is not the global optimum. Search spaces of typical optimisation problems contain lots of local optima.

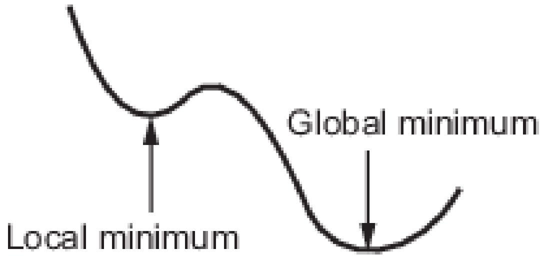

Figure 2.5: illustration of Local and Global Optima, assuming a minimisation problem [34]

2.2.1. Classification of Optimisation Models

An important step in any optimisation process is the classification of the optimisation model. Different optimisation models are usually characterised by different internal structures, which significantly influence the class of optimisation methods applied to them. Optimisation models can be classified based on a number of different metrics [32]:

1. **Deterministic versus Uncertain Optimisation**: In many optimisation problems, the data cannot be known accurately for a variety of reasons; the first reason may be due to simple errors in measurement. The second and more fundamental reason is that some data represents information about the future (e. g., product demand or price for a future time period) and simply cannot be known with certainty. Optimisation models are deterministic when all data to the model are known accurately throughout the process. In this thesis, the scope is limited to deterministic optimisation models with very little uncertainty. Although some aspects of a mobile network such as the wireless channel and the exact location of users in the service area are uncertain, to evaluate the performance of different heuristic algorithms, this uncertainty is removed by assuming a fixed snapshot of users and only taking into account the distant dependent path loss (between a user equipment and a base station) when modelling the wireless channel. This ensures that the algorithms are compared on exactly the same problem instance for fairness in the achieved results.

2. **Unconstrained versus Constrained Optimisation**: Optimisation problems can also be distinguished based on the number of constraints. Unconstrained optimisation problems in which the problem is formulated with no explicit constraints arise directly in many practical applications. Unconstrained optimisation problems can also arise from the re-formulation of constrained optimisation problems in which the constraints are replaced by penalty terms in the objective function. On the other hand, constrained optimisation problems have explicit constraints on the decision variables. The constraints on the variables can vary widely from simple bounds to systems of equalities and inequalities that model complex relationships among the variables. Constrained optimisation problems can be further classified according to the nature of the constraints (e.g., linear, nonlinear, convex) and the smoothness of the functions (e.g., differentiable or non-differentiable). The optimisation models presented in this thesis are constrained because the deployment of a base station network is usually subject to a number a given constraints such as the budget.

3. **Continuous versus Discrete Optimisation**: In many application areas the possible values of the decision variables can be modelled as a discrete set, often a subset of integers, whereas in other areas variables can take on any real value. Models with only discrete variables are discrete optimisation problems; models with continuous variables are continuous optimisation problems. Continuous optimisation problems tend to be easier to solve than discrete optimisation problems; the smoothness of the functions means that the objective function and constraint function values at a point x can be used to deduce information about points in a neighbourhood of x. The optimisation models presented in this thesis are discrete is nature because the deployment of a base station network is usually based on a number finite variable choices available to a mobile network operator.

4. **Single versus Multiple Objectives**: Many optimisation problems have a single objective function, however, many operational optimisation problems have multiple objective functions. Multi-objective optimisation problems arise in many fields (such as engineering, economics, and logistics etc.) when optimal decisions need to be taken in the presence of trade-offs between two or more conflicting objectives [35]. For example, in mobile network design, increasing the coverage footprint of a given network usually will involve the installation of more access points at strategic locations which in turn increases system cost. In this example, the optimisation presents two objectives; maximising coverage and minimising cost. In practice, problems with multiple objectives can be re-formulated as single objective problems by either forming a weighted combination of the different objectives or by replacing some of the objectives by constraints. Another approach to optimisation models with multiple objectives is to seek a '*Pareto front'*, which is a set of non-dominated feasible solutions to the problem [35].

5. **Complexities:** Another important criterion for classification of optimisation problems is their complexity class. A complexity class represents the set of all problems that can be solved using a given amount of computational resources. There are two important classes of problems: ***P*** and ***NP***.

   Definition 2.5: ***P*** class. The complexity class ***P*** is the set of all decision problems that can be solved by a deterministic machine in polynomial time [32].

   An algorithm (deterministic) is polynomial for a decision problem A if its worst complexity is bounded by a polynomial function $p(n)$ where n represents the size of the input instance [32]. Hence, the class ***P*** represents the family of problems where a known polynomial-time algorithm exists to solve the problem. Problems belonging to the class ***P*** are then relatively "easy" to solve and a global optimum solution can be found.

Definition 2.6: ***NP*** class. The complexity class ***NP*** represents the set of all decision problems that can be solved by a non-deterministic algorithm in polynomial time [36].

A non-deterministic algorithm can exhibit different outcomes on different executions even for the same input since there is no rigid specification of the search path. A decision problem $A \in \boldsymbol{NP}$ is ***NP****-complete* if all other problems of class ***NP*** are reduced polynomially to the problem A [32]. If a polynomial deterministic algorithm exists to solve a ***NP****-complete* problem, then all problems of class ***NP*** may be solved in polynomial time. ***NP****-hard* problems are optimisation problems whose associated decision problems are ***NP****-complete*. Most real-world operational optimisation problems (such as mobile network design problems) are ***NP****-hard*, for which provably efficient algorithms do not exist. They require exponential time (unless $\boldsymbol{P} = \boldsymbol{NP}$) to be solved to optimality. Meta-heuristics constitute an important alternative to solve this class of problems [32].

2.2.2. Optimisation methods

An optimisation problem may be solved by an approximate method or exact method, depending on its complexity and structure. Exact methods when applicable return global optimal solutions and guarantee their optimality. Approximate (or heuristic) methods, on the other hand, can generate good solutions in a reasonable time for practical use to complex problems where exact methods fail to scale, but there is no guarantee of finding a global optimum solution. Base station network planning optimisation problems are complex and difficult tasks that cannot be solved at scale using exact methods, hence, the focus is on heuristic algorithms. Heuristics methods can provide useful solutions to the task of base station network planning in practical time.

2.2.2.1. Approximate and Heuristic Methods

Some examples of exact methods include the following classical algorithms: dynamic programming, branch and bound algorithms, constraint programming, and A* family of search algorithms (A*, IDA*—iterative deepening algorithms) [37]. Exact methods can only be practically applied to small instances of difficult problems (***NP**-hard* problems) due to the sheer amount of computation resources that will be required as the problem size grows [38]. These type of difficult optimisation problems are more practically approached by approximate methods, which are able to find acceptable solutions within practical computational resources. Two sub-classes of approximate methods may be distinguished: ***approximation*** and ***heuristic*** algorithms. Heuristic algorithms can be further distinguished into problem-specific heuristics and meta-heuristics, and do not give any approximation guarantee on the quality of the obtained solution(s). In contrast, approximation algorithms return provable solution quality guarantee from the global optimum and provable run-time bounds *specific* to the target optimisation problem (problem dependent). This characteristic limits their applicability. Moreover, in practice, attainable approximations are too far from the globally optimal solution, making those algorithms not very useful for many real-life applications [32].

Definition 2.7: A *e*-approximation algorithm generates an approximate solution not less than a factor *e*-times the optimum solution [39]

2.2.2.2. Meta-heuristics

Meta-heuristics are general-purpose algorithms that can be applied to optimise almost any optimisation problem. They provide a general high-level methodology that can be used as a guiding strategy in designing underlying heuristics to solve specific optimisation problems. Unlike exact methods, meta-heuristics are more robust to scale (size) of problem instances by still returning satisfactory and practical solutions within acceptable computational time. However, solution quality is not guaranteed since they are heuristic algorithms. Moreover meta-heuristics *"may"* return global optimum solutions to some problem instances [40]. Meta-heuristics have received more and more popularity in the past 20 years, mainly because of their diverse application domains. Their use in many applications shows their efficiency and effectiveness to solve large and complex problems. A large number of different meta-heuristic algorithms have been proposed and studied in the literature on different optimisation problems.

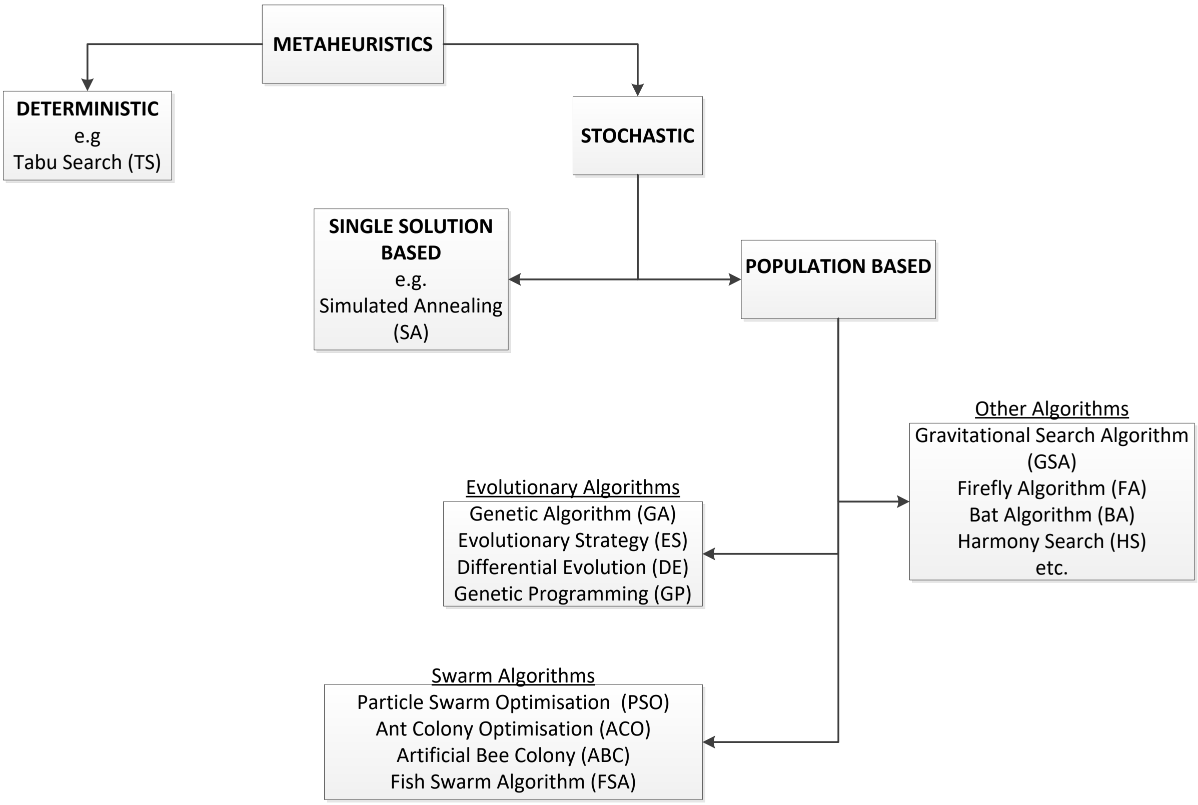

Figure 2.6: Taxonomy of meta-heuristic algorithms

Figure 2.6 shows taxonomy of *some* of the most popular meta-heuristic algorithms. The algorithms are generally inspired by a natural/physical phenomenon. Different types of meta-heuristics need to be studied to find the most suitable for a given optimisation problem.

2.2.2.3. Core Components of Meta-heuristics

Regardless of the meta-heuristic algorithm considered to solve a given optimisation problem, there are three core design questions common to all meta-heuristics in approaching an optimisation problem; *the solution encoding* (or *representatio*n), definition of *the objective* (or *fitness*) *function* that will guide the search, and the definition of *variation operators* that move the algorithm from one point in the search space to another.

1. **Solution encoding**: The solution encoding is the critical bridge between the problem model and the algorithm. It is a fundamental design question in the application of meta-heuristics and plays a major role in the efficiency and effectiveness of any meta-heuristic. The encoding must be suitable and relevant to the tackled optimisation problem. In fact, when defining an encoding, one has to bear in mind how the solution will be evaluated and how the variation operators will operate on it. Many alternative representations may exist for a given problem. [32] defined the following criteria for designing a solution encoding :

    - *Completeness*: All solutions in the search space of the problem must be represented by the encoding.
    - *Connexity*: A search path must exist between any two solutions of the search space.
    - *Efficiency*: The representation must be easy to manipulate by the search operators, such that the time and space complexities of the operators dealing with the encoding are reduced.

2. **Objective function and Constraint handling:** The objective (or fitness) function models the goal to be achieved [41]. It associates with each solution of the search space a real value that describes the quality or the *fitness* of the solution. The objective function is at

the heart of designing a meta-heuristic to solve an optimisation model. It will guide the search towards "good" solutions of the search space in the hope of finding the global optimum solution. If the objective function is improperly defined, it can lead to non-acceptable solutions whatever meta-heuristic is used [32]. Multi-objective optimisation problems have more than one objective function, however, it is not unusual to combine them into a single weighted objective function to be optimised. Most real word optimisation problems will have associated constraints that must not be violated for a candidate solution to be *feasible*. Dealing with constraints in optimisation problems is another important topic for the efficient design of meta-heuristics. The constraints may be of any kind; linear or non-linear, and equality or inequality constraints. A simple way to deal with constraints is to reject solutions to the model that do not meet the constraints [42]. However, this strategy may not be very effective for complex search spaces with large infeasible regions and disjoint feasible regions. A better constraint strategy is to apply a penalty to infeasible solutions during the search process. The unconstrained objective function is extended by a penalty function that will penalise infeasible solutions. This is the most popular strategy used in the literature. The definition of the penalty function and how it is applied is a design decision to be considered by the algorithm designer.

3. **Variation Operators:** Meta-heuristics require variation operators to move from one state to next in the search space. The variation operators work on the solution encoding and are designed based on the same. A common search operator to all Meta-heuristics is the *Neighbourhood* function. The *Neighbourhood* function of a solution s, $N'(s)$, creates a new solution s' by making a single change to one of the decision variables of s. The change to s is usually done in a random manner, however, problem specific knowledge may also be used in the definition of *Neighbourhood.*

2.2.2.4. Hill Climbing Algorithm (HC)

Algorithm 2.1: Hill Climbing Algorithm

```
Input:  Iter:Number of iterations
        Let x = a random solution
        For i = 0 to Iter-1
             Let f = fitness of x
                  Make a small change to x to make x'
             Let f' = fitness of new point x'
             If f' is better than f Then
                  Let x = x'
             End If
        End For
Output: The solution x
```

The Hill climbing algorithm follows the problem-solving heuristic of making the locally optimal choice at each stage [43]. The HC algorithm, as shown in the pseudo code[1] of Algorithm 2.1, starts at a random point in the search space and aims for a better fitness value of the objective function by randomly exploring its *neighbourhood*, accepting only of better points in the search space. The process continues until the maximum number of iterations or some other stopping criteria is reached. The HC finds the *neighbour* of a solution by making a small change to the current solution. For example, the decision of whether or not to place base stations on a set of 5 candidate sites, can be represented by a 5 bit binary string. Assuming the binary string is “1010”, a neighbour solution can be created by flipping the first bit to create a new binary string, “0010”. The HC is particularly simply in its approach (compared to other algorithms), however, the HC may become trapped at local points in the search space because of its greedy approach.

[1] Pseudo code is an implementation of an algorithm in the form of annotations and informative text written in plain English and has no syntax.

2.2.2.5. Simulated Annealing (SA)

Algorithm 2.2: The Simulated Annealing Algorithm

```
Input:  T0 : Starting temperature
        Iter: Number of iterations
        Λ: The cooling rate
        T = T0
   1.   Let x = a random solution
   2.   For i = 1 to Iter
   3.       Let f = fitness of x
   4.       Make a small change to x to make x′
   5.       Let f′ = fitness of new point x′
   6.       If f′ is worse than f Then
   7.           Let p = exp(-(fitness difference)/T)
   8.           If p < rand(0,1) Then
   9.                   Reject change (keep x and f)
   10.          Else
   11.              Accept change (keep x′ and f′)
   12.          End If
   13.      Else
   14.          Let x = x′
   15.      End If
   16.      Let T = Tλ
   17.  End For
Output: The solution x
```

Simulated Annealing (SA) [44] is a probabilistic meta-heuristic technique for approximating the global optimum of a given function. The idea of SA originated from the natural process of annealing in metallurgy, which involves heating materials to a very high temperature and then allowing them to slowly cool down to alter its physical structure. The SA algorithm, as shown in the pseudo code of Algorithm 2.2, has a temperature parameter that is kept to simulate the heating and cooling process in metallurgy; the temperature parameter along with the difference in fitness between two *neighbour* solutions is used to compute the probability of accepting a solution with a worse fitness following line 7 of Algorithm 2.2. The temperature variable is initially set to a high value, then steadily "*cooled*" in each iteration using a cooling rate (line 16, Algorithm 2.2) (i.e. the temperature decreases whilst running the algorithm). This temperature keeps decreasing towards zero by the end of the algorithm. At sufficiently low temperatures, the SA acts like the Hill climbing algorithm, accepting only better solutions. SA has been reported to be particularly suited to combinatorial search problems and has been previously used for network planning problems [45] [37].

2.2.2.6. Genetic Algorithm (GA)

Algorithm 2.3: Genetic Algorithm

```
Input:  T: Number of iterations
        Pz: population size
        P(t): Population in iteration t
   1.   Generate  Pz random solutions
   2.   While t < T
   3.   Evaluate P(t)
   4.   P_p (t)= P(t). Select parents()
   5.   P_c (t)=crossover (P_p)
   6.   P_c (t)= Mutate (P_c(t))
   7.   Evaluate (P_c(t))
   8.        P(t+1)= build next generation of size  Pz from
             P_c (t)  + P(t)
   9.   t= t+1
   10.  End  While
Output: Best solution in iteration T
```

A Genetic algorithm (GA) [46] is a meta-heuristic search technique inspired by natural evolution. The GA has been successfully applied to a wide range of real-world problems of significant complexity, too complex for exact methods. A GA operates on a population of often randomly generated solution representations known as *chromosome(s).* Each *chromosome* represents a solution to a problem and has a *fitness* (returned by the objective function), a real number which is a measure of how good a solution it is at addressing the particular optimisation problem. As shown in the pseudo code of Algorithm 2.3, starting from the generated population of chromosomes, a GA carries out a process of fitness-based selection and recombination to produce a successor population, referred to as the next *generation*. During recombination, parent chromosomes are selected and their genetic material (solution components) combined based on a crossover method to produce child chromosomes. These then pass into the successor population. As this process is iterated, a sequence of successive generations evolves and the average fitness of the chromosomes tends to improve until some stopping criterion is reached (often a maximum number of iterations). The fittest chromosome (i.e. the solution with the best objective value) in the ending population is returned as the optimal solution to the problem. In this way, a GA "evolves" the best solution to a given problem.

A. Parent Selection

The GA uses a selection operator to choose parent solutions that will breed to create the next (hopefully better) population of solutions. A widely used selection operator is the *Roulette wheel selection* [46]. In the *Roulette wheel selection,* parents are selected for breeding *based* on a fitness based probability wheel. In other words, the chance of a chromosome being selected is directly proportional to its fitness. Another selection operator is the *Tournament selection* [47]. In a *Tournament selection,* a chromosome is chosen as a parent after winning a fitness based *Tournament* of randomly chosen chromosomes in the current population. The optimal selection operator for a given problem can only be found through empirical experiments.

B. Crossover

The creation of an *offspring* population is at the core of the GA. A crossover operator generates a pair of offspring solutions from a pair of parent solutions. The crossover operator achieves this by combining the genes of the chosen parent solutions to create offspring. A gene is the smallest component of an encoding. The mechanism of combining the parent genes could be one point [46], two-point [48] or uniform [49] (Figure 2.7). Crossover is applied according to a given probability known as the *crossover probability*. Like the parent selection operator, the optimal crossover operator and probability for a given problem can only be found through empirical experiments.

C. Mutation

Mutation alters one or more gene values in a chromosome from its initial state. Unlike the crossover operator, this can result in entirely new gene values being added to the gene pool. Using mutation a Genetic algorithm may be able to escape a local optimal point in the search space. Similarly to the crossover operator, the mutation operator has a *mutation probability*. The *mutation probability* is a very small value, much smaller than the crossover probability. Following the example in Figure 2.7, mutation can be performed by simply flipping a bit according to the *mutation probability*.

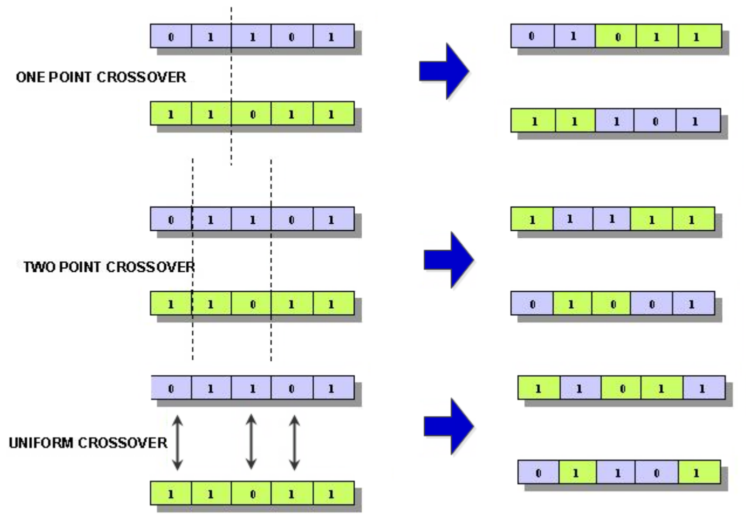

Figure 2.7: Crossover example on a simple binary encoding[50]

2.3. Summary

This chapter presented the background material necessary for the rest of this thesis. It started with an overview of the fundamentals of mobile cellular networks and discussed their evolution towards next-generation 5G mobile networks. Next, key technologies for 5G mobile networks that include a heterogeneous base station access network, small-cells, and MIMO were introduced. Finally, an overview on optimisation and the background on three meta-heuristic search techniques used later in the thesis have been presented.

3. Literature review: Cellular Base station Access Network Design

This chapter presents a literature review on cellular base station access network design optimisation with emphasis on the use of meta-heuristics and the transition to a heterogeneous base station mobile network architecture. The aim is to characterise research development over time, analyse the state of the art and position the contributions made in this thesis. Some key terms are also explicitly defined.

3.1. Introduction

Mobile network operators (MNOs) are constantly battling to optimise the *trade-off* between their network performance (as seen by their subscribers) and the cost of owning and operating their networks. Generally, to significantly improve the network performance of their systems or enter new markets, MNOs carry out tasks such as upgrading to more advanced equipment or increasing the density of base stations. This in turn undesirably increases their system cost of ownership, hence strategies that optimise this *trade-off* have continued to be highly sort after. Optimised network planning, especially at the base station network level[2], which leverages optimisation algorithms such as meta-heuristics for planning and operating the base stations has and will be a key strategy for optimising this *trade-off* in the future. The cost and performance implications of a typical cellular network are strongly dependent on the base station deployment, hence cellular network operators fundamentally carry out base station planning in order to establish or extend a base station topology that meets the required user equipment (UE) quality of service (QoS) metrics over a defined geographical area; while simultaneously minimising system cost of ownership. More recently, there has also been increased attention to the concept of 'on *demand* network

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[2] Henceforth, by 'network', we refer to a collection of base stations deployed on a defined geographical area to provide wireless cellular communication services to subscribers.

planning' to reduce power consumption and improve traffic load balance across the base stations [15].

Regardless of the use case, to improve the cost efficiency of mobile networks, operators have since adopted automatic methods (over manual methods) to carefully optimise design deployment of their base station and core networks, enabled by system simulation tools and application of optimisation problems and algorithms [51]. Such tools and algorithms are extremely important for determining a base station topology that provides the required QoS demands of users in cost effective way, and also for gaining better insights into how different technologies affect the *trade-off* between system performance and system cost. On that note, the literature in cellular base station network planning and optimisation has fundamentally focused on developing representative cellular system models that capture the *trade-off* between system cost and system performance, and development and study of optimisation models and algorithms in order to find an optimal network topology balance between system cost and performance, also known as *base station planning*. This thesis places emphasis on the later without completely ignoring the former. Although base station planning has been a well-studied research area, advancements in mobile network technology in recent years such as a heterogeneous base station access architecture, cell range expansion (CRE), MIMO and the need for denser base station deployments necessitate new system and problem models, insights, and algorithms/approaches for planning and operating cellular systems of the future.

In general, the task of automatic base station planning can be broken down into three key steps;

1. System modelling: Cost and Performance
2. Optimisation problem design: Objectives, Decision variables and Constraints
3. Algorithms for network optimisation

3.1.1. System Modelling: Cost and Performance

Different base station configurations are poised to affect the cost and QoS performance (as seen by the subscribers) of the network differently. Usually, high-performance configurations also incur high system cost in terms of capital expenditure and power consumption, and as such capturing this trade-off is crucial to the network planning process. In the following sub-sections, some key definitions are made, the literature on system cost and QoS performance modelling is reviewed with emphasises on heterogeneous base station access network.

3.1.1.1. QoS Performance modelling

The system level metrics used to measure the quality of service (QoS) experienced by subscribers of a mobile network in this thesis are the network *coverage* of the service area and the traffic handling *capacity* of the network.

A. Coverage Metric

The network *coverage* defines the reach or presence of a mobile network signal across the considered geographical area and is technically a measure of the received signal power from (and to) the base stations that should ideally be at or above a minimum radio frequency (RF) sensitivity level; beyond which wireless communication between the base station and a subscriber user equipment (UE) is not achievable. Cellular systems are designed to provide wide area wireless communication services for both stationary and nomadic subscribers, to achieve this objective, the base station network deployed by mobile network providers must provide sufficient *coverage* over the service area to guarantee wide area communication services. A widely adopted *Test Point* concept for modelling base station coverage in system simulation is proposed in [52]. In this concept, discrete *test points* densely distributed across the service area are used as RF signal measurement points. Test points that measure below the RF signal threshold from a given base station are said to be out of its coverage area, and as such subscribers in that region cannot access mobile network services through it (i.e. the base station).

B. Capacity Metric

In today's cellular system it is not sufficient to merely provide sufficient coverage. The *capacity* of the cellular system must also be assured and is a measure of the system's ability to deal with the traffic demand of its subscribers without compromising their experienced quality of service. In fact, the need to provide extremely high data traffic capacity in mobile networks is the key motivation for next-generation 5G mobile networks [53]. Base stations have a limited amount of resources such as bandwidth and transmission power which limits the maximum number of subscribers they can efficiently serve at any one time [54]. Consequently, like with the coverage, multiple base stations are required to provide sufficient capacity to subscribers. Next generation 5G mobile systems which must provide very high data capacity will be enabled by very dense base station deployments [20]. Earlier cellular systems such as GSM (Global System for Mobile Communication) were optimised mainly for wide-area wireless voice communication, however, driven by the success of internet connectivity and increasingly smart mobile terminals, the popularity of data traffic have since dwarfed voice [2]. Hence by traffic, we refer to the data transfer speed of a mobile network measured in bits per unit of time. A standard theoretically measure of the wireless link (between a base station and a mobile terminal) data transfer capacity of a cellular system is the Shannon capacity theorem given by equation 3.1 [55];

$$R(\text{bps}) = W\log_2\left(1+\frac{S}{N}\right) \tag{3.1}$$

Where R is the theoretical maximum capacity of the channel (in bits/second), W is the bandwidth of the channel in Hertz, (S) is the desired signal power in Watts and (N) is the noise power, also in Watts. The ratio (S/N) is also known as the Signal to Noise Ratio and indicates the strength of the desired signal in comparison to Noise and interference (N), as measured at the receiver. Interference arises from simultaneous data transmissions on the same frequency block by neighbouring base stations. The Shannon capacity limit defines the theoretical upper bound at which data bits can be transmitted across the link with acceptable bit error probability. Clearly, the channel capacity is limited by the bandwidth and the signal to noise power level. It is shown later that the link capacity limit can be increased using multi antenna spatial multiplexing between the base station and the mobile terminal with MIMO technology.

To better characterise base station capacity, a measure of its *load* is defined for LTE cellular standard. The *load* of a base station is a function of the number of users in its cell, their data requirements and their signal to noise ratios [56]. The *load* of a base station measures the average utilization level of the transmission resources used in serving the demand of all active user equipment within its cell [57]. Hence subscribers connected to an *over loaded* base station may still suffer poor QoS even if they achieve good coverage and suffer little interference.

3.1.1.2. Base station Deployment Cost Modelling

A complete quantification of the deployment *cost* of a cellular radio access network (RAN) is difficult to perform. Certain cost components depend on factors that are not easily quantifiable, such as the contractual relationship between hardware manufacturer and operator, or the regulatory and legislative environment in the country of deployment. Furthermore, the RAN deployment cost can be shared between different mobile network operators by employing approaches like flexible spectrum sharing, roaming, and infrastructure sharing. Nevertheless, some key cost aspects of the RAN can be approximated with reasonable accuracy using mathematical relationships. These mathematical cost models discussed subsequently in this section form the basis of cellular base station deployment simulation tools and analysis. The objective is to capture the relationship between the cost implication of a mobile network deployment and its QoS performance under different cellular system technologies, as realistically and efficiently as possible. This plays an important role in evaluating the cost-performance *trade-off* of changing technologies, architectures, frequency bands, etc. in practical scenarios.

The cost of owning and operating a mobile network also known as the total cost of ownership (TCO) can be broken into two main categories [21]; capital or infrastructural cost (CAPEX) and operational cost (OPEX). A number of research publications have reported power consumption cost (i.e. electricity bill) to be a major contributor to the OPEX of a typical mobile network [10]. Over the last two decades cellular mobile networks have evolved from 1st Generation (1G) to current state of the art LTE –Advanced 4G OFDMA based systems, incorporating more and more advanced technologies aimed at improving various system performance metrics. Current 4G LTE based cellular systems were standardised to provide significantly higher data capacity over previous cellular system generations. Advanced technologies such as heterogonous base station radio access networks enabled by the introduction of small-cell base stations (e.g. pico, femto, relay base stations), interference mitigation techniques, massive MIMO, co-operative multi-point transmission (CoMP), cloud-radio access network etc. have been introduced into the system to increase data carrying capacity and coverage. However, despite the system performance gains these technologies bring, adopting them also influences the OPEX and CAPEX for mobile network operators. Consequently, models that relate their system QoS performance gain to system cost are central for cost efficient base station deployment. With particular emphasis on heterogeneous networks, the following key contributions in literature are reviewed. The authors of [58] proposed a simple linear model for measuring the TCO of a traditional homogenous cellular system as function of the number of base stations deployed, the annualized cost of spectrum, energy and the annual cost per BS. However their work does not consider heterogeneous networks since the type of base station will impact on the TCO in this case. Furthermore, their model abstracts the individual base station configurations which should also be taken into account. For example a base station site with multiple sectors and antennas will certainly incur more costs than a simpler configuration base station even though they are of the same type. In [59] the authors take into account the influence of different types of base stations on the CAPEX cost by defining the cost of micro base stations as a fraction of the macro base station cost. They also propose the idea of deployment efficiency, which is the network capacity performance normalised by the TCO incurred. However, similar to [58], their work abstracts the impact of individual base station configurations which should be taken into account. In his well-cited work [60], Johnson proposed a discounted cost model for mobile networks based on heterogeneous base station access network architecture, which is used to account for inflation and the time value of money. However, his work does not explicitly consider the impact of power consumption. Based on the work of [60], Nikolikj in [61] presented dollar estimates of CAPEX cost for the different classes of base stations in a heterogeneous access network. In conclusion, the main limitation of these works (above) is the fact that they cover only limited RAN configurations and do not capture the impact of base station complexity on the cost of the system. A cost model that captures more configurations and also the impact of increasing complexity of base station setup, usually tailored at improving the network QoS performance, on the network cost is very desirable to improve the accuracy of conclusions reached.

3.1.2. Problem Modelling and Optimisation

To overcome the complexity associated with the large number of base station variables that should be taken into account in order to optimally design/plan and operate mobile networks, the task of base station planning is viewed as an optimisation problem. This allows optimisation algorithms to be applied to various aspects of cellular network planning to improve accuracy and speed. The earliest cellular systems were manually planned based on the experience of engineers. However, the need for a more automatic and optimised framework for deploying base stations was quickly realised as the complexity of cellular systems increased [62]. Such optimisation tools for network deployment and management are key for next-generation 5G cellular networks, which are expected to transfer extremely large amounts of data at high speeds; from both a performance and cost perspective [20]. The key methodology for achieving this objective of automation can be broken down into two main steps (see Figure 3.1); (i) the formulation of practical system optimisation problems (ii) and application/development of efficient algorithms/tools to solve them, of which meta-heuristics constitute an import class.

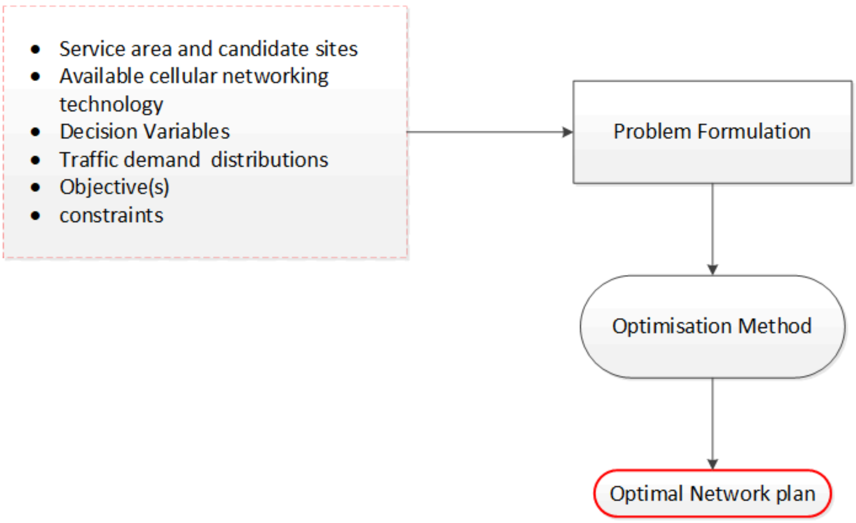


Figure 3.1: Automatic base station planning methodology

In the first step, the objective is to formulate practical optimisation problems that influence the structure of the base station network, while the second step aims to develop efficient algorithms capable of finding the optimal operating values to the decision variables subject to the given constraints (as defined in step one). The basic idea is to deploy/design a network of base stations over a defined geographical area taking into account the user subscriber population demand and available cellular system technologies. The result of this process is a deterministic set of network parameters (such as the number, locations, transmission power etc.) of base stations that not only influence the quality of service (QoS) performance of the system but also the cost incurred by network operators. In essence, the optimisation problem model *poses* a network design question for which algorithms can be developed to answer. Over the last two decades, a number of base station planning optimisation problems have been proposed and studied in literature, engineered based on different cellular standards, scenarios and objectives.

3.1.2.1. 2G and 3G base station planning

The first base station planning problem was based on the 2nd Generation(2G) GSM standard and was motivated by the need to provide wide area mobile network coverage at a reduced cost [40][63][64]. The key decision variables were to optimise the number and locations of base stations such that network coverage is maximized while minimising the number of base stations used. The models were based on some variant of the *un-capacitated set cover problem*, which has been shown to be ***NP****-hard* [65] and thus motivated the application of heuristics/ meta-heuristics. A large number of different heuristic methods have been published for tackling the GSM base station planning problem. Dedicated heuristic algorithms have been proposed by a range of authors [66],[67], [68]. However, approaching the problem using meta-heuristic algorithms was the most popular approach. The work in [40] established CHC [69] meta-heuristic as the optimal technique after empirically analysing its performance against a Simulated annealing algorithm and Genetic algorithm for solving the GSM base station problem, through empirical simulations. However, their work only assumed a perfectly uniform network structure, which is not realistic. The authors in [64] proposed a multi-objective hybrid framework for applying meta-heuristics to solve the GSM base station planning problem and analysed the performance NGSA-II[35], SPEA2 [70] and PESA [71] to generate the *pareto-front* between achieving higher coverage and minimising cost, and found comparable performance between them. The hybrid framework was based on an integer permutation solution encoding, a problem specific greedy decoding algorithm and a meta-heuristic algorithm. However, the performance of their framework against the standard application of meta-heuristic was not reported. The main drawback of this strategy is that the performance of the meta-heuristic is limited by the intelligence of the greedy decoder. The work in [63] showed that the speed of a Genetic algorithm at tackling the base station planning problem can be improved through execution parallelisation. The works in [72] and [45] showed the application of Simulated annealing to GSM and 3G base station planning problems respectively. The 3G base station planning problem introduced additional complexity to the GSM problem. In GSM mobile network design, the issue of *capacity* was tackled in a separate optimisation problem known as the *frequency assignment problem* [73], hence the capacity issue was ignored in the problem formulation for base station deployment. As earlier mentioned in the background section (2.1.1), 3G systems were based on single frequency reuse and as such there was a need to consider the level of interference between base station cells and traffic handling capacity of the network in the problem formulation [74]. The 3G base station planning problem which is also ***NP****-hard* was tackled in [74] and [75], using a tabu search algorithm [76]. However, the solution encoding was not clearly defined. The works in [77][78] showed the application and effectiveness of the Genetic algorithm for solving the 3G base station planning problem, using a binary and an integer solution encoding respectively. The work in [79] considered the 3G base station planning problem from both the downlink and uplink perspectives and analysed the performance of four meta-heuristic algorithms, Genetic algorithm, Simulated annealing and evolutionary Simulated annealing after 10000 fitness calls. They report the Simulated annealing algorithm to be better than the Genetic algorithm in terms of mean fitness and standard deviation. However, their problem model reduced the level of automation by fixing the number of base stations to deploy and only optimising their locations. A more robust model should also determine the number of sites deployed. Furthermore, their experiment set only considers a very small network instance with only 95 possible base station locations and the algorithms are only analysed on a uniform traffic distribution, which is not realistic to make conclusions applicable to real mobile networks. In fact, in most of the literature, this criticism is upheld. Another drawback of the literature is the lack of benchmark data to allow a holistic comparison of the approaches. The above literature, which is by no means exhaustive but certainly representative, shows that the base station planning problem in 2G and 3G mobile standards has been well investigated and the application of meta-heuristic to them has been extensive.

3.1.2.2. Heterogeneous base station planning

2G and 3G base station planning models were both based on a *homogeneous flat* network architecture including only macro base stations. Macro base stations have large coverage areas, high power consumption and CAPEX cost implications. A *flat* architecture consists of base stations of the *same* type and which have similar/identical coverage areas and cost implications. In contrast, current 4G LTE mobile networks have been standardised based on a multi-tier heterogeneous base station access network architecture consisting of traditional macro base stations and heterogeneous *small-cell* base stations (micro, pico and femto) with local coverage areas. A dense multi-tier heterogeneous access network architecture is one of the key technologies in next-generation 5G mobile networks system for achieving the "*extreme*" data capacity requirement [19]. The deployment of heterogeneous nodes in 5G systems will have a significantly higher density than today's conventional networks [80]. In addition, many advanced technologies have been introduced into the network architecture (such as co-operative multi-point transmission (CoMP), MIMO, cell range expansion, advanced interference mitigation etc.). The holistic 5G heterogeneous system architecture taking into account the expected high density of base stations and advanced technologies presents a more complex planning environment and requires a paradigm shift from the base station planning models/approach of conventional flat networks if mobile network operators are to deliver 5G in a cost efficient manner.

A key leverage of a 5G base station planning framework will be the ability to exploit *heterogeneous* base station types and *small-cell base stations* for different traffic scenarios. Hence an important sub-problem model that has been considered by a number of authors for 5G is to determine the locations and number of *small-cell* base stations to deploy in an existing macro-cellular network [81][82][83]. However, this problem model only considers a single aspect of the 5G base station deployment problem. Multiple types of base stations (such as macro, pico, femto and relay base stations) which have different characteristics (see section 2.1.3.1) should be exploited when formulating the base station planning problem for 5G. Hence the "*type*" of base station to deploy would be a key decision variable. In addition, the optimal operating parameters (such as the transmission power etc.) of these base stations must also be considered, as well as other advanced cellular networking concepts key to 5G. The other key enabler for a 5G base station planning framework will be a clear framework for applying heuristic algorithms to support decision making for 5G base station deployment. The 5G problem inherits the complexity of flat network design, which has been proven severally to be ***NP**-hard*; and introduces additional dimensions to the problem. This complexity and the expected high density of base stations in 5G motivate the application of heuristic algorithms over exact methods. Heuristics and meta-heuristics have been extensively studied and established for base station planning of conventional flat architecture based mobile networks. However, their application to the 5G heterogeneous access environment has not been clearly established. The authors in [84] proposed approximation algorithms to select a subset of candidate sites to deploy macro or small cells to minimize the total cost of ownership (TCO) of the cellular system while satisfying coverage and capacity constraints. However, their work simplifies the 5G network planning task. For example, their work assumes that the base station transmit power is always fixed and that the type of base station to install in each candidate site is known. Furthermore their work does not consider the optimisation of key 5G technologies like cell range extension (CRE) and MIMO. The authors in [85],[86] and [87] formulate the same problem as in [84] as a multi-objective problem and tackle it using different metaheuristic algorithms. The main criticism of these works is the simplicity of the network planning problem model assumed which is inadequate for proper planning of a 5G network. Furthermore, 5G networks will leverage multiple key technologies like MIMO and CRE which is not considered in these work. Moreover, the use of metaheuristic for online network management is not given any consideration in these works. This thesis attempts to fill these gaps by proposing a clear framework for *exploiting* heterogeneity in 5G base station planning by *jointly* optimizing heterogeneous base station architecture, MIMO and Cell range extension, using meta-heuristics.

3.2. Summary

This chapter reviewed research development in mobile network base station planning starting from the early models based on the 2G cellular standard, analysed the state of the art and positioned the contribution of this thesis while defining key concepts. The development of 2G and 3G base station planning problems were based on the conventional flat network and the application of meta-heuristic has been extensive. However, base station planning problems based on conventional flat network design are not optimised for planning 4G and next-generation 5G mobile networks which are based multi-tier heterogeneous base station network architecture. In addition, many advanced technologies have also been introduced in the RAN and as such more sophisticated base station planning models are required for efficient planning of 5G networks.

4. 5G Heterogeneous Base station planning System Model with CRE

4.1. Introduction

The motivation of this chapter is to describe the cost and QoS performance system model used in the rest of this thesis for deployment analysis of a 5G mobile network with heterogeneous base stations and cell range extension technology. The user QoS performance metric used are the network coverage and the average throughput of users. This chapter does not include novel contributions and only describes the computation of key metrics and assumptions used in the analysis of 5G in this thesis.

The system model for a 5G cellular network with heterogeneous base stations and cell range extension technology described in this chapter is based on the 4G LTE-Advanced cellular downlink standard [31]. The LTE-Advanced standard is the most advanced release defined for 4G LTE and is adopted as the air interface in this project since a 5G air interface has not been standardised. Moreover, the 5G standard is expected to inherit and extend most of the technologies in the LTE-Advanced standard [88]. We explicitly consider mathematical representations of two advanced LTE-Advanced features; small base station *cell range expansion* and a *multi-tier heterogeneous base station access architecture* in the proposed system model, which are considered key technologies in next-generation 5G mobile networks [19]. The system model proposed is generic to both greenfield and expansion base station planning but presented with emphases on the downlink of a LTE-Advanced mobile network, assuming a greenfield scenario and is derived by unifying existing models from the literature (discussed in section 3.1.1). The described system model explicitly relates system cost and QoS performance modelling of a mobile network as a function of the base station deployment and forms the basis for all the conclusions reached in this thesis. That is, for a given base station topology (deployment), the system model returns the system cost and performance implications with respect to the traffic scenario.

4.1.1. Proposed 5G System Model based on LTE-Advanced

A 3D simulation area, *A*, is considered with sets of discrete test points in Cartesian coordinates (*x*,*y*,*z*). The simulation area model represents a defined geographical area where 5G base stations are to be deployed. Different types of base stations (macro, micro and pico) can be deployed and configured to provide cellular service to subscribers. It is assumed that the candidate locations (candidate sites) where these base stations can be installed are known and given as input to the model, hence the focus is on the question of "*how to cost effectively deploy the base stations without violating the quality of service metrics?*" The assumption on candidate sites is valid as in practice, mobile network operators will only have a finite set of locations for installing base stations as opposed to complete freedom.

U	Set of demand nodes/points (DN)
M	Set of candidate sites for macro base station deployment
S	Set of candidate sites for small-cell deployment[3]
N	Set of base station *models/types*
v_i	Site acquisition cost of site $i \in M \cup S$
b_i	Backhaul cost of site i
e_n	RF equipment cost of BS *model* $n \in N$
P	Discrete set of possible transmission power levels of base stations
D	Discrete set of deployed base stations
ρ^u	Signal to interference and noise ratio of DN $u \in U$
ω^{max}	Maximum achievable spectral efficiency
W	Available bandwidth
Cov'	Service area coverage percentage requirement
Cap'	Capacity requirement
δ	RF sensitivity limit
B	Set of possible bias values for CRE
C	Discrete set of coverage test points

Table 4.1: System model variables

The types of base stations considered are grouped into two classes, tier 1 (macro base

[3] The phrase *small cells* refers to all other types of base stations except the macro base station

stations) and tier 2 (small-cell base stations). Conventional cellular standards were only based on tier 1 base stations. The small-cell base station models considered are *micro* and *pico* base stations. For clarity, the notation y and $\hat{y}$ is used for macro and small-cell base station variables, respectively, where the distinction is necessary. The following describe the system model;

1. A "*network*" or "*cell plan*" is made up of base station sites deployed with base stations to provide cellular service to a set U of demand nodes distributed on the service area. A demand node (or point) aggregates traffic from active users in a small area. The demand point concept proposed in [89] has become a widely accepted method for simulating cellular traffic. For simplicity it assumed that every base station deployed forms only one cell, hence the terms *base station* and *cell* are used interchangeably.

2. The set U of demand points in a region is static for every simulation and represents a *snapshot* of the spatial distribution of users at a particular time. This is a reasonable assumption as the cellular network subscriber distribution is usually statistically stable for fixed intervals [90]. Base station network planning is usually carried out on the worst case traffic scenario in order to build robustness into the network design[4].

3. Demand nodes connect to base stations in order to receive data bits. Unless stated otherwise, every demand node associates to and is served by one base station in every simulation.

4. For simplicity, it assumed that all base stations use the equal resource allocation policy, hence, all active user equipment served by a given base station receive an equal allocation of its transmission resources.

[4] The worst case traffic scenario is the time period when the network experiences the most data demand from its subscribers

5. Each candidate base station site is defined by 2 variables; (a) *x*,*y*,*z* coordinates and (b) site acquisition cost. The cost of site acquisition for small-cells is significantly cheaper than for macro sites [7]. Legacy sites may or may not exist; they do not have site acquisition cost as they are already deployed, however, the base stations deployed add to the power consumption cost of the network.

4.1.2. Base station Models and Configurations

In each candidate macro site $(m \in M)$, it is assumed that mobile operators can deploy an omnidirectional macro base station operating with a transmission power level $P_t \in P$. While in each candidate small-cell site ($s \in S$), one of $|\widehat{N}|$ *models* for small-cell base stations can be deployed, operating with a transmission power level $P_t \in \hat{P}$. Each small-cell *model* represents a different *type* of small-cell base station with a different power consumption profile, communication range (i.e. maximum transmit power) and equipment cost.

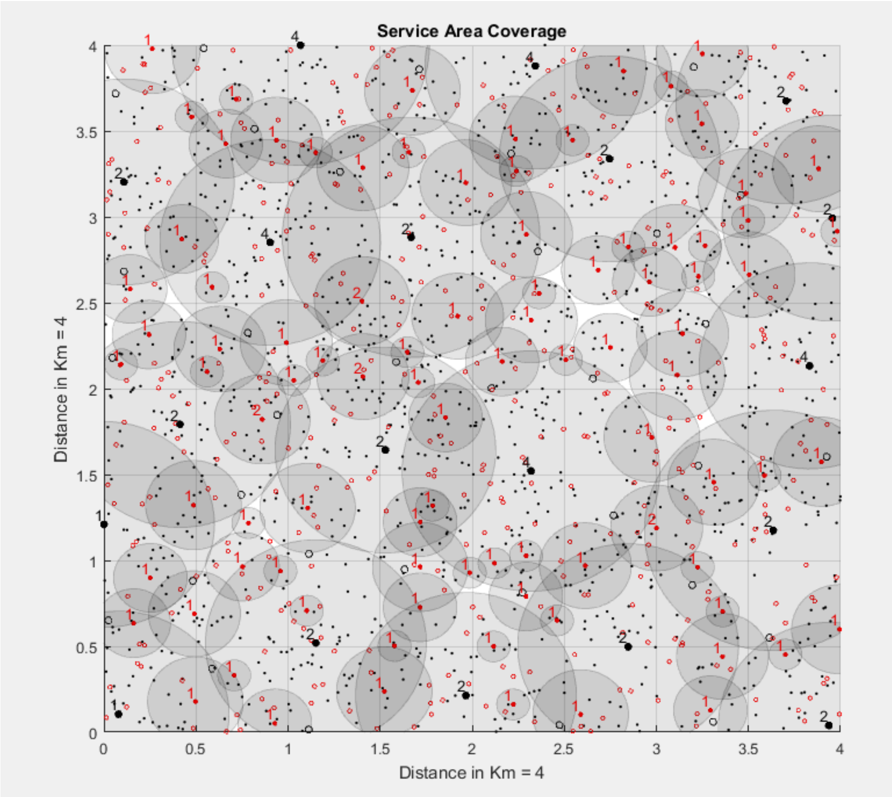


Figure 4.1: Service area (A). Black and red dots are candidate macro and small cell locations, respectively. Filled dots indicate deployed sites

4.1.3. Link Modelling

To model the link between a base station and an active subscriber (represented by a demand point), the Hata path loss model for metropolitan areas is adopted [91]. However, other propagation models can also be used. The downlink received signal power by a demand point $u \in U$ from a base station deployed in site $m \in M$ and can be described by equation 4.1 [92].

$$P_{rx(m,u)}[\text{dBm}] = 10\log_{10}\left(\frac{P_t G_{tx}}{N_{sub}}\right) + 30 - \sigma_{feed} + H_{(m,u)} \tag{4.1}$$

$$H_{(m,u)}\,[\text{dB}] = -(\text{PL}_{m,u} + \sigma_{m,u} + \text{L}_{pen}) \tag{4.2}$$

P_t is the transmission power of the base station (in Watts) and G_{tx} is transmitter gain multiplier while $H_{(m,u)}$ is the channel gain between the base station m and user $u \in U$. The channel gain $H_{(m,u)}$ comprises the deterministic distance dependent path loss $\mathrm{PL}_{m,u}$ and $\sigma_{m,u}$ is a zero-mean Gaussian random variable that models the effect of shadowing. L_{pen} models the outdoor to indoor penetration loss experienced by users accessing cellular services from indoor areas. σ_{feed} is the transmitter feeder cable loss. N_{sub} is the number of OFDMA subcarriers in the considered bandwidth.

4.1.4. Cell Association with CRE feature

An important decision variable for the quality of service (QoS) received by a user equipment is the decision on which base station it connects. Although LTE-Advanced allows co-ordinated multi-base station data transmission (CoMP) unless otherwise stated it is simply assumed that user equipment (demand point) can only be linked to one BS and consequently receives data from only that BS at a time. To aid the problem formulation, let the binary matrix $\boldsymbol{a}$ represent the demand point to BS associations such that $a_{(d,u)}$ determines if the demand point $u \in U$ is associated to base station $d \in D$, were the variable is "1" if it does or "0" otherwise. In conventional cellular network architecture (without small-cell base stations), a user equipment u associates to a base station d_u from which it receives the strongest downlink pilot power, according to equation 4.3;

$$d_u = \arg\max_d \left(P_{rx(d,u)}\right) \mid P_{rx(d,u)} \geq \delta \ \ \forall d \in D \tag{4.3}$$

$$d_u = \arg\max_d \left(\beta_d + P_{rx(d,u}\right) \mid P_{rx(d,u)} \geq \delta \tag{4.4}$$

However, due to the very small transmission power (cell sizes) of small-cell base stations (compared to macro base stations), *cell range extension* is defined for small-cell networks (also known as *cell biasing*, see section 2.1.3.4). The use of cell *biasing* allows small-cell base stations to attract more users. The LTE-Advanced standard defines the concept of *biasing* for all base station types, however, it is assumed that only small-cell base stations utilise cell *biasing* technology, consequently, the *bias* value for a macro base station is zero. Consequently, equation 4.3 is modified to equation 4.4. β_d is the bias value (in decibels) set for base station d. Note that biasing *does not* increase the transmission power of the small-cell base station but simply *entices* more user equipment to connect to the small-cell layer of base stations thereby offloading the macro layer base stations. The use of small-cell *biasing* avoids an artificial capacity crunch that may be created by overloaded macro base stations and is considered key in 5G mobile network design.

4.1.5. Quality of Service Performance Metrics

This sub-section defines the metrics used for quantifying the quality of service (QoS) performance of a network in terms of its ability to provide the required coverage and the required capacity to meet the demand from its subscribers.

4.1.5.1. Network Coverage

To model signal coverage over the service area, a set *C*, of dense and uniformly distributed points on the service area that ***should*** receive radio frequency (RF) signal power from at least one base station above a given RF (radio frequency) sensitivity limit, δ, is defined. The percentage of points in *C* that are covered defines the degree of coverage of the network, which should be maximised. Clearly, the highest coverage that can be achieved is 100% and is computed by equation (4.6).

$$\Upsilon_{d,c} = \begin{cases} 1, & \text{if point c } (c \in C) \text{ is covered by BS } d \\ 0, & otherwise \end{cases} \tag{4.5}$$

$$Coverage = \left(\frac{\sum_{d}^{|D|} \sum_{c}^{|C|} \Upsilon_{d,c}}{|C|} \right) .100 \tag{4.6}$$

4.1.5.2. Network Capacity

The *network capacity* defines the traffic handling capability of the network. The download speeds of users from a given base station are a function of the available bandwidth, the number of users in its cell, data requirements, and their experienced *signal to noise ratio* (ρ). Overloaded base stations may provide connected users with poor quality of service (QoS). The proposed capacity metric is to maximise the downlink average network user throughput (equation 4.7), which is a fairer metric for experienced user data speeds than sum throughput often used in literature. N_u is the number of demand nodes served by the same base station cell as $u \in U$. AV is the average network user throughput. The maximum spectral efficiency $\omega^{\max}$ is set by limiting the maximum possible value of experienced signal to noise

$$AV = \frac{\sum_{u}^{|U|} R_u}{|U|} \tag{4.7}$$

$$R_u = \left(\frac{W}{N_u}\right).\omega \tag{4.8}$$

$$\omega = \min\left(\log_2(1 + \rho^u), \omega^{\max}\right) \tag{4.9}$$

ratio to 30dB.

4.1.5.3. Power Consumption

Minimising the power consumption of cellular networks is one of the key design performance metrics in 5G for both economic and environmental reasons[19]. The huge density of base stations that will be deployed in a 5G mobile network is poised to significantly increase the power consumption cost. To model the network power consumption, the power model from [93] which describes detailed power consumption profiles for different types of base stations as a function of their parameters, is adopted.

Parameters	Macro	Micro	Pico
ϑ_{PA} (amplifier efficiency) [%]	31.1	22.8	6.7
σ_{feed} (Feeder loss) [dB]	-3	0	0
P_{RF} [W]	12.9	6.5	1.0
P_{BB} [W]	29.6	27.3	3.0
σ_{DC} [%]	7.5	7.5	9.0
σ_{MS} [%]	9.0	9.0	11.0
σ_{cool} [%]	10.0	0.0	0.0

Table 4.2: base station power consumption parameters [93]

$$PC = N_{TX} \frac{\frac{P_t}{\vartheta_{PA}.(1-\sigma_{feed})} + P_{RF} + P_{BB}}{(1-\sigma_{DC})(1-\sigma_{MS})(1-\sigma_{cool})} \quad (4.10)$$

The power consumption of the network is mainly a function of the number, *type*/*model*, transmit power and the number of transmitter chains ($N_{TX} = 1, for\ now$) of the deployed base stations. Given the BS model $n \in N$ and the base station transmit power P_t let the power consumption of BS d be given by the function $PC_d = PC(n, P_t, N_{TX})$.

4.2. Summary

This chapter described a system model for deployment analysis of 5G cellular networks with heterogeneous base stations based on the 4G LTE-Advanced cellular downlink standard. We explicitly show the mathematical representations of two advanced LTE features; small-cell range expansion and a multi-tier heterogeneous base station architecture in the proposed model, which are key technologies in next-generation 5G mobile networks. The proposed model, which is derived by unifying existing literature, explicitly relates cost and QoS performance modelling of a mobile network as a function of the base station deployment and forms the basis for all the conclusions reached hereafter. That is, for a given base station topology, the system model returns the system cost and QoS performance implications with respect to the traffic scenario.

5. Meta-heuristic for planning 5G Heterogeneous access network with cell range extension

5.1. Introduction

The 5G mobile network standard is to be developed with the concept of “broadband access everywhere” providing typical user download data rates of at least 50-100 Mbps everywhere, and much higher in ideal scenarios[20]. In addition to other advanced technologies, a consensus capacity solution for 5G between industry and academia is to densify the base station (BS) cells in a given area [7]. However, this hike in the deployment of base stations will also lead to an immense increase in capital cost (CAPEX) and power consumption, which accounts for the majority of operational cost (OPEX) for a typical mobile network operator (MNO) [94]. Traditional long-range base stations (henceforth referred to as macro BSs) account for over 60% of power usage in a typical cellular system in addition to expensive site acquisition and equipment costs [21]. The high power consumption of telecommunication networks also implies an increase in CO_2 emissions in the environment. A heterogeneous access network, which combines standard long-range macro base stations and low range base stations (known as small-cells) has been standardised as a key 5G technology to cost-efficiently increase system capacity of current and future mobile cellular networks [7]. Small-cell BSs have significantly lower power consumption, site acquisition, equipment cost, range and size than standard macro base stations and are designed to provide local coverage and capacity. Next generation 5G cellular networks, which must deliver on extreme capacity requirement are predicted to consist of a high density of heterogeneous small-cell deployments, with some scholars even envisaging a total elimination of traditional macro base stations [59]. In any case, the optimal deployment in such a network should achieve very high coverage and capacity both for outdoor and indoor users; while simultaneously minimising CAPEX and OPEX cost. A key enabling feature standardised by 3GPP for heterogeneous base station access network is the technology for small-cell range extension (CRE). In CRE, a positive cell selection offset is used by small-cells to attract more users. The major benefit of CRE is to ensure that small-cells actually serve enough users that would otherwise have been served by the macro base stations. However excessive cell range extension can potentially increase interference strength and consequently decrease overall system throughput if no additional interference mitigation techniques are employed. Finding the optimal CRE value for every deployed small-cell base station results in a complex optimisation problem in its own right [95]

Considering the discussion (above) on the requirements of 5G, cost efficient deployment of 5G base stations will be very essential to mobile operators but significantly more complex than traditional mobile networks and motivates the novel application of heuristics techniques. Traditional base station planning schemes, which are based on flat homogenous design are not optimised to deal with planning a 5G cellular access network architecture, which will consist of a high density of heterogeneous network nodes (i.e. base stations) and advanced features such as CRE extension. Hence, the objective/contributions of this chapter are twofold;

1. To provide an optimisation framework for the application of heuristic search for the deployment of 5G heterogeneous base station deployment taking into account cell range extension feature of small-cells. The framework, which is generic to both greenfield and expansion network planning is made up of an integer programming problem, which is designed towards exploiting base station heterogeneity; a solution encoding, and a fitness function.
2. To analyse the performance of meta-heuristics algorithms (Simulated annealing, Hill claiming and Genetic algorithm) as base station deployment/planning tools for 5G. Meta-

heuristics algorithms were widely used for planning conventional networks (see 3.1.2.1), however, their application to the 5G environment is an open research area.

The most related literature to the work of this chapter are the works in [96] and [87]. In [96], the authors proposed an integer programming optimisation model for exploiting base station heterogeneity in the design of cost efficient cellular networks. However, their problem model does not include cell range extension. Furthermore, no heuristic algorithms were presented for optimising the model. The authors in [87] considered the application of meta-heuristic for optimising the deployment of a heterogeneous base station access network, however, their problem does not include cell range extension. Furthermore, their model which does not take into account network power consumption assumes that base station transmit power is fixed, which simplifies the problem. Moreover, this work did not explicitly present an integer programming model to the problem. This chapter builds and extends on these works.

5.2. System Model Recap

The system model and assumptions defined in chapter 4 are adopted unless explicitly stated otherwise. The system model captures the key deployment aspects of a heterogeneous base station cellular access network as a key technology of next-generation 5G cellular architecture. To model this *heterogeneity*, different *models* of base stations are considered. These models are operator owned base stations with different characteristics such as cost, power consumption and coverage. Two classes of base station models are considered; traditional *macro-cell* base stations with large coverage and high power consumption, and *small-cell* base stations with much smaller coverage footprint and significantly lower cost. Two *kinds* of small-cell base stations are considered based on their coverage footprint, *micro* and *pico* small-cells. Cellular operators through a *network planning scheme* can exploit the characteristics of the different *models* of base stations to design a high capacity but cost efficient cellular access architecture.

5.3. 5G Heterogeneous Network planning Problem Formulation with CRE

The objective of the 5G network planning problem is to design a cellular wireless access network by deterministically finding the optimal number, locations, *types*, transmission powers (the base station transmission power determines its cell radius) of base stations to deploy in a given service area to provide a certain level of capacity and coverage while minimising power consumption and CAPEX cost. The 5G network planning problem model also includes optimisation of CRE bias value for each small-cell base station deployed, which substantially expands the problem search space. In the problem model defined below, operators aim to exploit the *different* kinds of base stations (i.e. base station heterogeneity) and small-cell range extension feature to design a high capacity but cost efficient base station network.

M	Set of candidate sites for macro base station deployment
S	Set of candidate sites for small-cell deployment[5]
L	Set of all candidate sites $L \in M \cup S$
N	Set of base station *models/types*
v_i	Site acquisition cost of site $i \in M \cup S$
b_i	Backhaul cost of site i
e_n	RF equipment cost of BS *model* $n \in N$
P	Discrete set of possible transmission power levels of base stations
D	Discrete set of deployed base stations
Cov'	Service area coverage percentage requirement
Cap'	Capacity requirement
B	Set of possible bias values for CRE
C	Discrete set of coverage test points
PC	BS power consumption function

Table 5.1: 5G network planning problem formulation variables

[5] The phrase *small cells* refers to all other types of base stations except the macro base station

The notation y and $\hat{y}$ is used to differentiate the variables for macro sites and small-cell sites, respectively, where necessary. All variables used are defined in Table 5.1. The following decision variables are introduced to facilitate mathematical representation;

- *Site deployment variable*: $\boldsymbol{x}$ is a deployment vector that indicates if a candidate site is deployed with a base station or not.

$$x_i = \begin{cases} 1, & \text{if a BS is deployed in site } i \in L \\ 0, & otherwise \end{cases} \tag{5.1}$$

- *Base station deployment variable*: $\boldsymbol{z}$ is a deployment matrix that indicates the model of base station deployed in each site.

$$z_{in} = \begin{cases} 1, & \text{if a BS of model } n \in N \text{ is deployed in site } i \in L \\ 0, & otherwise \end{cases} \tag{5.2}$$

- *Power deployment variable*: $\boldsymbol{j}$ is a deployment matrix that indicates the transmission power of deployed base stations.

$$j_{pd} = \begin{cases} 1, & \text{if a BS } d \text{ uses power level } p \in P \text{ }, d \in D \\ 0, & otherwise \end{cases} \tag{5.3}$$

- *CRE deployment variable*: $\boldsymbol{k}$ is a deployment matrix that indicates the CRE value of deployed small-cell base stations.

$$k_{bd} = \begin{cases} 1, & \text{if a small BS } d \text{ uses bias level } b, b \in B \\ 0, & otherwises \end{cases} \tag{5.4}$$

5.3.1. Objectives

The following are the objectives considered to the optimisation problem:

$$\mathrm{C1} = \sum_{m \in M}^{|M|} x_m \sum_{n \in N}^{|N|} z_{mn} \left(e_n + (v_m + b_m)\right) \tag{5.5}$$

$$\text{C2} = \sum_{s\in S}^{|S|} x_s \sum_{n\in \hat{N}}^{|\hat{N}|} z_{sn} \left(e_n + (v_s + b_s)\right) \tag{5.6}$$

$$\textbf{CAPEX}: \min_{\boldsymbol{x},\boldsymbol{z}} \ [\text{C1} + \text{C2}] \tag{5.7}$$

$$\text{P1} = \sum_{s}^{|S|} x_s \sum_{n}^{|\hat{N}|} z_{sn} \sum_{p}^{|\hat{P}|} j_{pd}\, PC(n, p, 1) \tag{5.8}$$

$$\text{P2} = \sum_{m}^{|M|} x_m \sum_{n}^{|N|} z_{mn} \sum_{p}^{|P|} j_{pd}\, PC(n, p, 1) \tag{5.9}$$

$$\textbf{Power}: \min_{\boldsymbol{x},\boldsymbol{j},\boldsymbol{z},\boldsymbol{k}} \text{P1} + \text{P2} \tag{5.10}$$

5.3.2. Constraints

Constraint (5.11) requires the service area coverage to be met by requiring its signal coverage to meet a given percentage threshold (Cov').

$$\left(\sum_{d=1}^{|D|} \sum_{c=1}^{|C|} \Upsilon_{dc}\right) \geq \ Cov' \tag{5.11}$$

Constraint (5.12) requires the capacity target to be met by ensuring the average user throughput meets a given minimum value (Cap').

$$AV \geq \ Cap' \tag{5.12}$$

Constraint (5.13) states that only one base station model can be deployed at any site.

$$\sum_{n=1}^{|N|} z_{in} \leq 1 \ \forall i \in L \tag{5.13}$$

Constraint (5.14) states that a deployed base station can only use one power level at a time.

$$\sum_{p=1}^{|P|} j_{dp} = 1 \; \forall d \in D \tag{5.14}$$

Constraint (5.15) states that a deployed small-cell base station can only use up to one CRE level at a time.

$$\textstyle\sum_{b=1}^{|B|} k_{b,d} \leq 1 \; \forall d \in \; \widehat{D} \tag{5.15}$$

Constraint (5.16) states that a user only associates to one BS at a time

$$\sum_{d=1}^{|D|} a_{du} \leq 1 \tag{5.16}$$

Constraint (5.17) states that a user can only associate to a deployed BS

$$a_{du} \; < \; 1 \; \forall u, d \notin D \tag{5.17}$$

5.4. 5G deployment using the stochastic meta-heuristic approach

The 5G base station problem has a significantly bigger search space than traditional base station deployment problems due to the number of decision variables and the high density of candidate sites that will be needed to provide extreme levels of user capacity in 5G. For example, a scenario with merely ‘30’ candidate base stations sites and ‘5’ possible site configurations has a solution search space of 5^{30}. This means that for every candidate site one of 5 BS configurations can be chosen to form the network. The 5G base station network architecture has introduced new BS configuration variables (which are not seen in a conventional mobile network) such as the *type* of base station to deploy, thereby significantly expanding the search space for finding an optimal network planning solution. Meta-heuristic algorithms offer a general and robust approach to tackling many large scale and complex optimisation problems where exact methods cannot be applied. However, their successful application in 5G cellular architecture depends on novel problem representation, the design of efficient search operators, tuning and comparisons between different algorithms, and incorporation of problem specific knowledge. Hence, this section starts by proposing a core framework for the application of meta-heuristics to 5G network planning based on the problem defined in section 5.3. The framework includes; the definition of the *solution encoding*, *fitness function* and *search operators*. The framework provides an integral structure for applying any type of meta-heuristics/heuristics to tackle the problem. Finally, the performance of three different algorithms is compared in terms of *optimality* and *efficiency*. The algorithms considered are; Simulated annealing, Genetic algorithm and Hill climbing algorithms. A random sampling approach is also developed as a baseline approach for analysing the effectiveness of the considered algorithms.

5.4.1. Meta-heuristics Framework

The proposed 5G deployment meta-heuristic framework is described in the following steps;

5.4.1.1. Solution Encoding

The first step in the proposed 5G deployment meta-heuristic framework is the *solution encoding*. An integer matrix representation where the deployment configuration of every candidate site is represented by an integer row vector, is proposed and shown in Figure 5.1. The integer matrix represents the configurations of an arbitrary deployment of base stations for which the cost and performance implications are computed as given by chapter 4 and section 5.3.

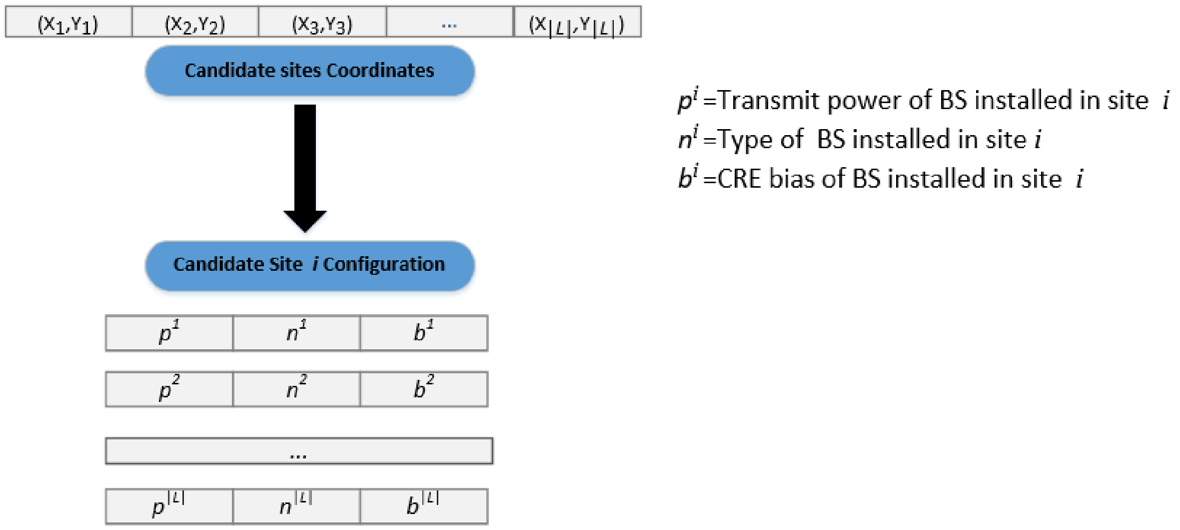


Figure 5.1: Illustration of proposed solution encoding (L is the set of all candidate sites)

The matrix has the same number of rows as the *total* number of candidate base station sites ($|L|$), such that the deployment configuration for the i^{th} candidate site is given by the i^{th} row of the matrix. In this chapter, four configurations per site are considered; the deployment variable, the base station model (n), the BS transmission power level (p) and the CRE value (b) for small-cell base stations. The deployment variable is fused with the transmission power such that the site where $p = 0$ is not deployed. Figure 5.2 illustrates the decoding of the solution encoding. A code book is consulted to translate the integer matrix into a network solution. The *neighbourhood* function (see section 2.2.2.3) creates a network solution s', from a current solution s, by changing the value of an arbitrary configuration of s. For example, with reference to Figure 5.2, the 'site A' *power* variable could be changed from 43 to 0, which removes the site from the resulting network plan. For this project, all *neighbourhood* changes are *stochastic*. Future work will consider the design of *intelligent* *neighbourhood* changes. The *crossover* operator (only relevant to the Genetic algorithm) creates new network solutions by combining configurations from two existing network solutions, as illustrated in section 2.2.2.6.

BS Model code
1=Macro BS
2=Micro
3=Pico

	Power	BS model	CRE
Site A	43	1	0
Site B	38	2	5
Site C	22	3	4
Site D	0	2	4

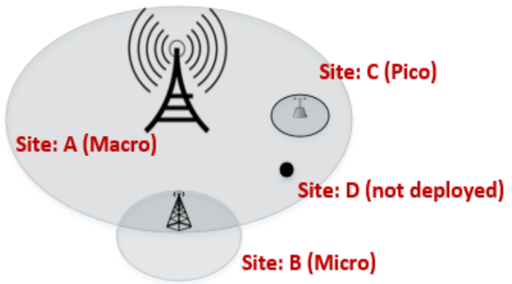


Figure 5.2: Illustration of solution decoding

5.4.1.2. Fitness Function

$$F = Cost + (K_1 Cap) + (K_2{}^{Cov}) \tag{5.18}$$

$$Cov = Coverage\ Target - Achieved\ Coverage$$
$$Cov = \max\{0, Cov\}$$
$$Cap = Capacity\ Target - Achieved\ Capacity$$
$$Cap = \max\{0, Cap\}$$

At the heart of the framework is a fitness function, which is used to quantify the *quality* of a candidate solution to the 5G deployment problem, in terms of the objective values and constraint violations. The proposed fitness function (F) which is to be *minimised*, penalises solutions that do not meet the *coverage* and *capacity* requirement constraints provided as input to the model; when both requirements are satisfied, the fitness function simply minimises the *cost* of the implied network. K_1 and K_2 are penalty magnitudes for the capacity and coverage constraints, respectively. Setting the values for K_1 and K_2 is fairly straight forward as long as equation (5.19) applies for both. *K* stands for either K_1 or K_2.

$$K.Gap > cost \tag{5.19}$$

The 'Gap' is the difference between the target coverage/capacity and the achieved coverage/capacity computed in equation 5.18. The '*cost*' term can either be the network power consumption, the CAPEX or a combination of the two. The exact combination function will be dependent on the preference of the mobile network operator or the financial implications. A simple and logical combination function is to convert the power consumption of the network in a particular time period H (for example, hours in one year) to an energy bill and add it to the Capital expenditure of the network as shown in equation 5.21. ϵ is the effective working period probability of a base station i.e. the probability that a base stations is fully operational or in *sleep* mode. It is assumed that small-cell base stations can be switched into *sleep mode* at extremely off peak times, however switching macro-cell base stations into *sleep mode* has been shown to be impractical because of their large coverage areas [97]. Hence $\epsilon = 1$, 0.5 is for macro and small-cell base stations respectively. η is the energy price per kilo watt hour. CAPEX is the total capital expenditure as computed in equation 5.7. D is the set of deployed base stations. PC_d is the power consumption of base station d.

$$E_{cost} = \sum_{d \in D}^{|D|} PC_d \epsilon H \tag{5.20}$$

$$cost = \text{CAPEX} + (E_{cost} \,.\, \eta) \tag{5.21}$$

5.5. Evaluation of Algorithms and Discussions

In this section, the performance of three (3) meta-heuristic algorithms, namely; Simulated annealing, Genetic algorithm and Hill climbing algorithms are analysed using the core framework outlined above. These algorithms were chosen based on their wide application to optimising 2G and 3G base station models (see section 3.1.2.1). Details on the algorithms have been provided in the background chapter 2. The algorithms are compared in terms of their *optimality* and *efficiency* to the 5G deployment problem. Finding *optimal* network topologies will be very important in 5G design as this can save mobile network operators huge deployment capital expenditure and operational maintenance cost and is indeed the main metric considered in this thesis. However, to improve system performance through load balancing and reduce network power consumption, 5G network will incorporate self-organising ability (basically real-time base station *management*) in response to traffic conditions [98]. This application context requires base station deployment algorithms that are *efficient* i.e. they can return 'good' network solutions in a short space of time and with reduced computational effort. The efficiency of algorithms was not considered in the design of earlier cellular standards, however the efficiency of algorithms is an important metric for the design of 5G since there is a need and capability to manage the status of base stations on demand. The main novelty of this section is the analyses of the considered heuristic algorithms from both an offline and an online perspective for 5G design.

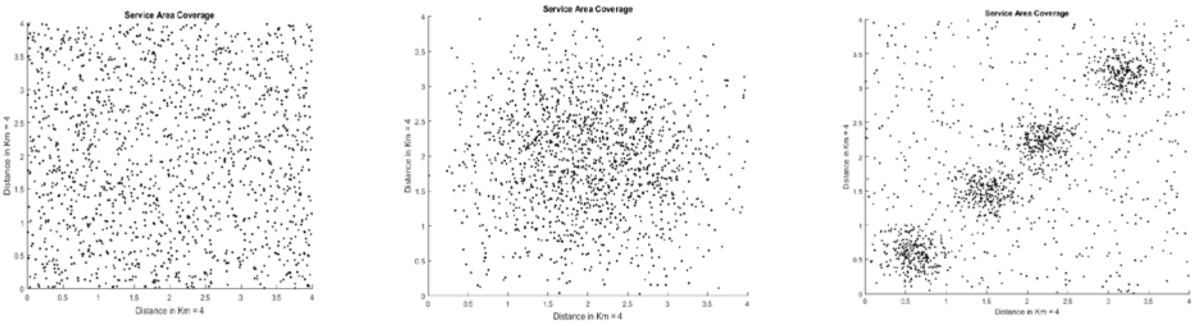
A random sampling approach (Algorithm 5.1) is developed as a baseline approach for analysing the performance of all the meta-heuristic algorithms considered.

5.5.1. Experimental setup

Parameter	Small	Large
Number Of Macro BS Sites	52	178
Number Of Small BS Sites	100	1000
Total	152	1178
Capacity Requirement (Mbps) $\boldsymbol{Cap'}$	5	50
Coverage Requirement (%) $\boldsymbol{Cov'}$	99	

Table 5.2: Parameters used for problem instances

The performance of each algorithm is analysed using a range of engineered test problems after 25 independent runs using the fitness function described in section 5.4.1.2. Test problems are distinguished by the density of candidate sites and distribution of demand nodes in a 16km^2 service area (see Table 5.2). Two (2) densities are used to simulate “Small” and “Large” problem instances. For each test problem class, three traffic demand patterns are drawn from three different distributions (Figure 5.3): a Uniform distribution, a Gaussian distribution, and multi-Gaussian distribution.



Uniform **Gaussian** **Multi-Gaussian**

Figure 5.3: Traffic demand distributions

In the Uniform distribution, users are distributed randomly but uniformly over the entire service area. The Gaussian distribution simulates a single hotspot traffic scenario with user density at a maximum in the centre, and gradually decreasing toward the boundary of the area. The multi-Gaussian distribution models a scenario with multiple hotspots. Additionally, each class of test problem has the required coverage and capacity target that must be satisfied as hard constraints. The system parameters used for the evaluation are shown in Table 5.4 and Table 5.3. To quantify the *optimality* of the algorithms, each algorithm is run for a maximum of 500,000 fitness calls in each run, which was large enough to ensure convergence. The number of fitness (*nf*) calls is a practical measure of an algorithm's computational effort especially when the time it takes to re-compute the network metrics is much larger than every other algorithm step as expected in a real-world application. To assess the *efficiency* of the algorithms, each algorithm is also run for a maximum of 100,000 fitness calls in each simulation run. An additional stopping criterion of 50,000 iterations of unchanged best-found solution is also introduced. The RSM approach is run for two (2) million fitness calls on each test problem and used as a baseline.

Parameter	**Values**		
Frequency	1.8 GHz		
Macro/small BS/ UE height	31m / 5m/ 1m		
RF sensitivity limit δ	-110dBm		
Bandwidth	50Mhz/tier		
K_1	1		
K_2	20000		
Base station Types	**Macro BS**	**Micro BS**	**Pico BS**
Max. Cell radius (Km)	0.6	0.18	0.05
Max. Power (dBm)	46	38	22
Power levels (dBm)	46,43,40	38	22
Antenna Gain dB	18	6	6
CRE config. (dBm)	NA	0,1,2,3,4,5	0,1,2,3,4,5
Equipment Cost (£)	40,000	0.3* MacroBS	0.1* MacroBS
Site Cost (£)	100,000	0.3* MacroBS	0.05*MacroBS
Backhaul (£)	15000	150000	15000
Energy unit price (£), η	0.13		

Table 5.3: Simulation Parameters

Distribution	Centroid(s)	Standard deviation
Gaussian	(2.0,2.0)	0.8
Multi-Gaussian	(0.5,0.5) (1.5,1.5) (2.3,2.3) (3.5,35)	0.3

Table 5.4: Parameters for Gaussian distributions

Parameter	GA	SA	HC
Max. Number of Fitness calls (*nf*) (Iter)	500,000 and 100,000		
Population size	1000	NA	NA
Selection	Roulette Wheel	NA	NA
Crossover/percentage	Uniform/100%	NA	NA
Mutation percentage/probability	100%/0.25	NA	NA
Start Temp T_0	NA	0.025	NA
End Temp T_E	NA	0.00005	NA
Cooling rate (SA only) Λ	Solve for x : $(x^{nf})T_0=T_E$		
Inner Loop	1000		

Table 5.5: Algorithm Parameters

5.5.2. Random Sampling Approach (RSM)

Ideally, the performance of the considered algorithms should be evaluated using the global optimum solution. However, finding the global optimum solution is not feasible due to the complexity of the problem and the extremely large search space. As suggested in [32], a Random Sampling Approach (RSM) is developed as a baseline for comparing the performance of the meta-heuristic algorithms considered. In RSM, *k* candidate solutions to the problem are randomly generated and evaluated based on the fitness function (see Algorithm 5.1). This approach can represent a manual approach to planning where *k* experts try to guess the optimal network architecture.

Algorithm 5.1: Random Sampling Algorithm (RSM)

```
Input:  k:   Maximum Number of samples
        f'= positive infinity
        For i = 0 to k-1
               Let x = a random solution
               Let f = fitness of x
               If f is less than f' Then
                      Let x' = x
                      Let f' = f
               End If
        End For
Output: The solution x'
```

5.5.3. Results and Discussion

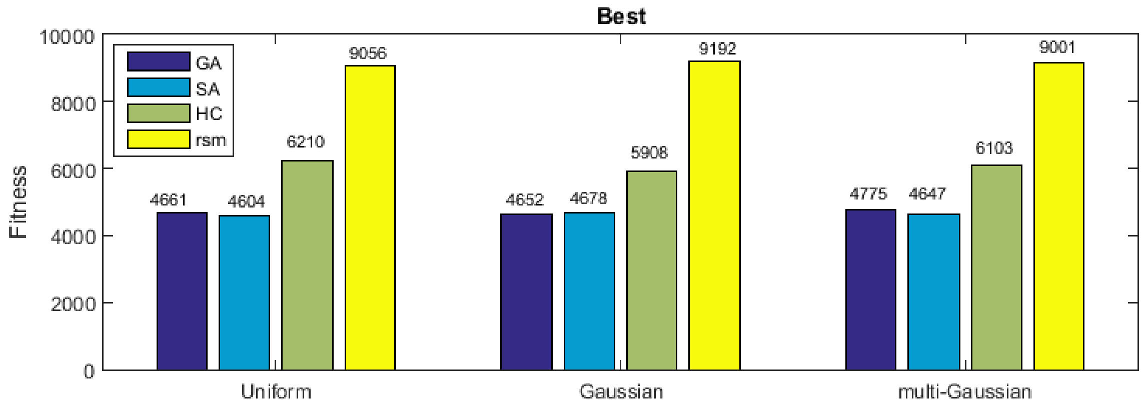


Figure 5.4: Comparison of Best run for each algorithm on Small instance. (rsm is the same as RSM)

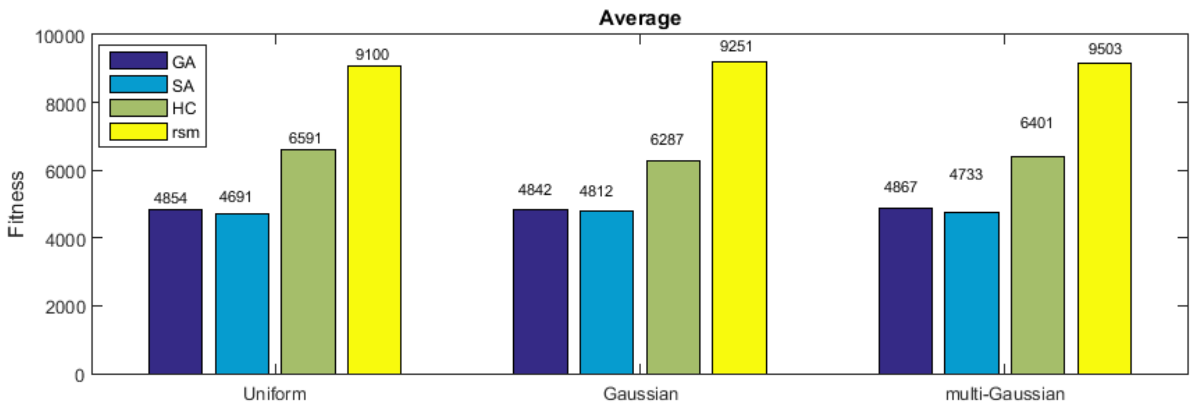


Figure 5.5: Comparison of Average of 25 runs for each algorithm on Small problem instance

Uniform traffic distribution						
Algorithm	**Fitness**	**Coverage (%)**	**Capacity (Mbps)**	**Power(kWh)**	**CAPEX(M£)**	**Success (%)**
RSM (baseline)	9056.10	98.5	5.00	111440.00	8.197	100
GA	4661.28	98.6	5.01	93492.32	4.580	100
SA	4604.24	98.8	5.00	95714.42	4.580	100
HC	6210.82	99.1	5.00	90924.84	6.198	100
Gaussian traffic distribution						
RSM (baseline)	9192.10	98.4	5.00	117750.00	8.772	100
GA	4652.00	98.8	5.00	93561.00	4.630	100
SA	4678.30	98.6	5.00	92081.00	4.628	100
HC	5908.10	99.1	5.00	93254.00	5.900	100
Multi-Gaussian traffic distribution						
RSM (baseline)	9001.00	98.5	5.00	101440.00	8.097	100
GA	4775.00	98.9	5.09	94764.00	4.760	100
SA	4647.00	98.8	5.06	95783.00	4.628	100
HC	6103.80	99.0	5.00	89757.00	6.091	100

Table 5.6: Comparison of Algorithms using best run (Small problem instance)

Results in Figure 5.4 and Figure 5.5 show the best and average fitness performance of the four different approaches across the different traffic demand distribution patterns on the Small problem instance, using the stopping criteria of 500,000 fitness calls. As seen in Table 5.6, all approaches achieved a 100% success rate on all runs in that they were able to return feasible network topologies that obeyed the coverage and capacity constraints. However, it is easy to see that the random sampling approach (RSM) returns network solutions with the worst fitness across the different user demand distribution patterns. On average, the RSM approach returned networks with a worse fitness than the Simulated annealing (SA) by almost 100%. The poor performance of the RSM is not unconnected to its *non-evolving* approach. In every iteration, the algorithm generates a random network solution (from the search space) and evaluates its fitness. Essentially, there is no evolution mechanism between topologies in successive iterations, which results in a random guess at each iteration. The Genetic algorithm (GA) and the Simulated annealing (SA) showed very comparable fitness values, across the different problem instances. The greedy Hill climbing (HC) algorithm consistently returned a worse network than the GA and the SA. For example, on the Uniform traffic instance, the HC returns a network with about 35% higher total cost than the SA. The main drawback of the Hill climbing algorithm is the lack of a mechanism for escaping a local optimal point in the search space.

	#Macro BS	#Micro BS	#Pico BS
GA	28.3	0.0	11.0
SA	28.0	0.0	11.3
HC	37.7	1.7	5.3

Table 5.7: Comparison of network structure (Small problem instance). The network structure describes the optimal base station topology return by an algorithm.

As reported in Table 5.7, the GA and SA designed almost identical network structures of mainly macro base stations (70%) complemented with pico base stations while the HC deployed a higher density of macro base stations (about 82% of the total base stations deployed). Overall, all the algorithms designed network solutions with a higher number of macro base stations despite a higher number of available small-cell candidate sites in the problem instance. This is mainly due to the fact the Small problem instance is coverage oriented with a low capacity requirement and as such macro base stations with large coverage footprints are preferred over local base stations. The Small instance is less typical of the 5G deployment problem due to the low capacity requirement and low site density, however, it is useful to understand the topology features under low capacity requirement and the performance of the algorithms in a relatively small search space.

	#Macro BS	#Micro BS	#Pico BS
GA	31.0	56.0	164.3
SA	32.3	48.7	159.7
HC	57.7	118.3	98.7

Table 5.8: Comparison Table of network structure (Large problem instance).

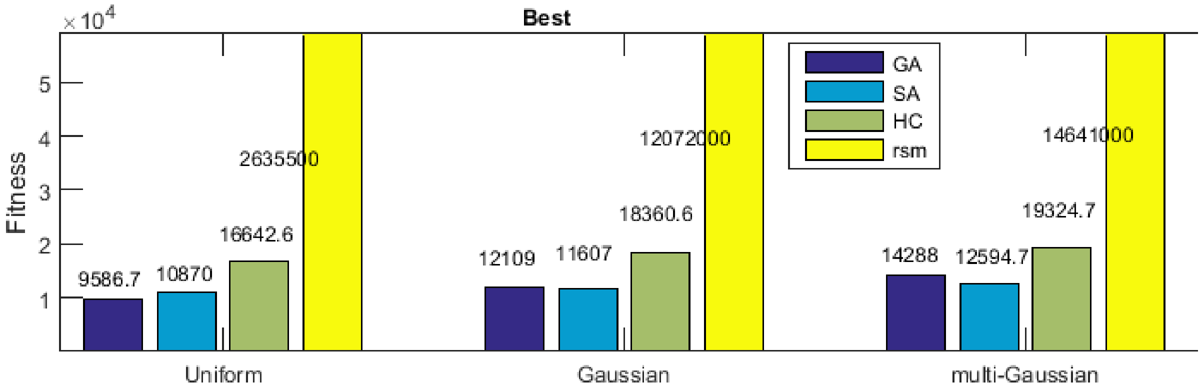


Figure 5.6: Comparison of Best run for each algorithm on Large problem instance

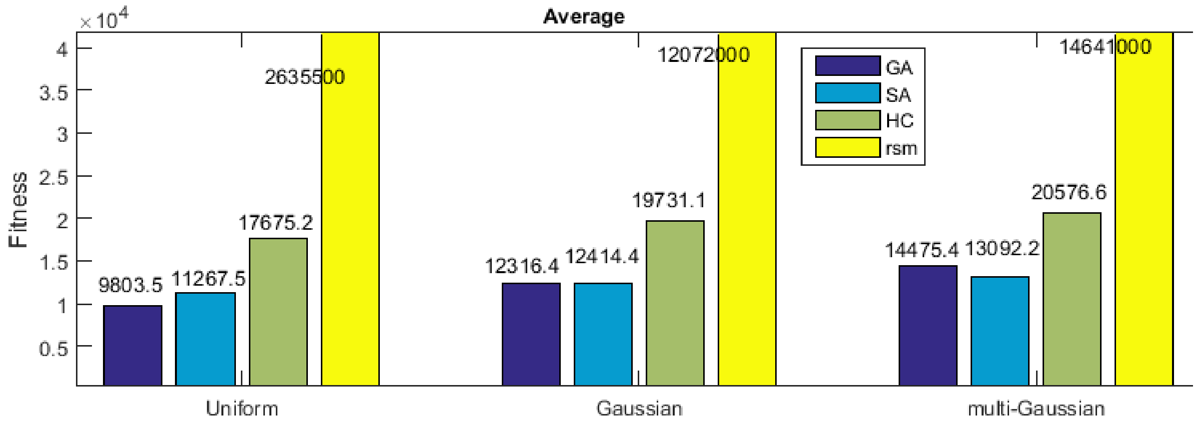


Figure 5.7: Comparison of Average of 25 runs for each algorithm on Large problem instance

The Large problem instance better characterises the 5G deployment problem, which is expected to consist of a high density of base stations and at least 50Mbps average user throughput requirement. Results in Figure 5.6 and Figure 5.7 show the best and average fitness performance of the four different approaches across the different user distribution patterns on the Large problem instance using stopping criteria of 500,000 fitness calls. A similar fitness graph to the Small problem instance is observed, with the RSM approach achieving the worst fitness performance, followed by the HC while the GA and the SA show comparable performance. Due to the significantly larger search space of the Large problem instance, the RSM approach, which essentially attempts to guess the optimal network topology in each iteration was found to be ineffective with 0% success rate in terms of its ability to design a network that satisfies the coverage and capacity requirements. On average, the RSM approach returned a network with a worse fitness than the Simulated annealing (SA) by almost 79707.5% on the Large problem instance compared to 100% on the Small problem instance.

Uniform traffic distribution						
Algorithm	**Fitness**	**Coverage (%)**	**Capacity (Mbps)**	**Power (kWh)**	**CAPEX(M£)**	**Success (%)**
RSM (baseline)	2635500.00	99.9	47.0	374050.00	46.000	0
GA	9586.78	98.6	50.0	95632.65	9.536	100
SA	10870.00	98.6	50.0	100900.00	10.819	100
HC	16642.62	98.6	50.0	132799.80	16.587	100
Gaussian traffic distribution						
RSM (baseline)	12072000.00	100.0	38.0	359060.00	47.600	0
GA	12109.00	98.6	50.0	118190.00	12.055	100
SA	11607.00	98.6	50.0	104690.00	11.524	100
HC	18360.60	98.6	50.0	155778.90	18.302	100
Multi-Gaussian traffic distribution						
RSM (baseline)	14641000	100.0	35.4	349220	47.300	0
GA	14288	98.6	50.0	134810	14.232	100
SA	12595	98.6	50.0	120559	12.510	100
HC	19325	98.6	50.0	164616	19.265	100

Table 5.9: Comparison of Algorithms using best run (Large problem instance)

The significantly worst performance of the RSM is a result of the much larger search space of Large problem instance. This result shows the RSM to be an ineffective approach for the planning of dense 5G mobile networks. The HC algorithm returns network topologies with a worse fitness (on average) across the traffic demand patterns by approximately 51% and 55% than the GA and SA respectively. The GA performed better on average than SA by 11.8% on the Uniform traffic distribution and 0.79% on the Gaussian traffic distribution. However, the SA was found to perform better than GA on the multi-Gaussian traffic distribution 9.5%. These results demonstrate that the Simulated annealing and Genetic algorithm to be the most effective of the evaluated approaches for offline planning of 5G where their relative performance depends on the traffic scenario.

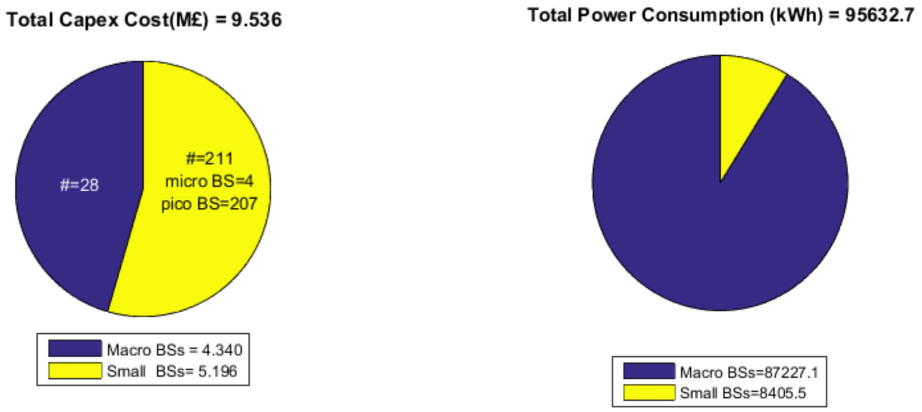


Figure 5.8: cost break down of the network topology returned by *GA* on Large uniform instance

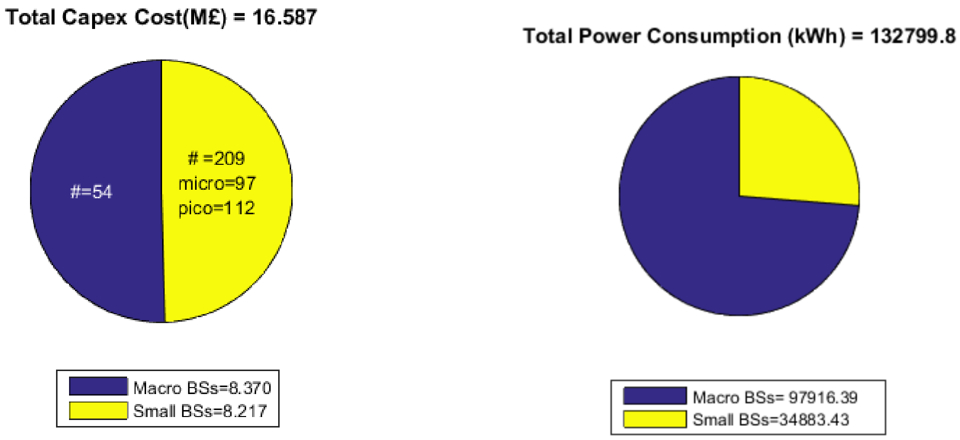


Figure 5.9: cost break down of the network topology returned by the HC on *Large* uniform instance

To gain insight into the relationship between the network structure and the CAPEX cost and power consumption of the network, Figure 5.8 and Figure 5.9 show the cost breakdown of the network topology returned by GA and HC on Large uniform problem instance respectively. It can be seen that for the same scenario, the GA deployed a network topology with 42.5% less CAPEX cost and 27.9% less power consumption than the HC. It can also be observed that the network topologies returned by the algorithms mainly differ in the density of macro base stations and the types of small-cell base stations deployed. Furthermore, it can be clearly seen that the CAPEX cost and power consumption is mainly influenced by the density of macro base stations used in the network topology. For example, the network topology returned by the network GA algorithm consists of only 28 macro base stations out of the 239 total base station deployed, yet account for about 92% of the network power consumption and about 45.5% of the CAPEX cost. This result suggests that finding the optimal density of macro base stations may lead to more CAPEX efficient and power consumption aware network topologies.

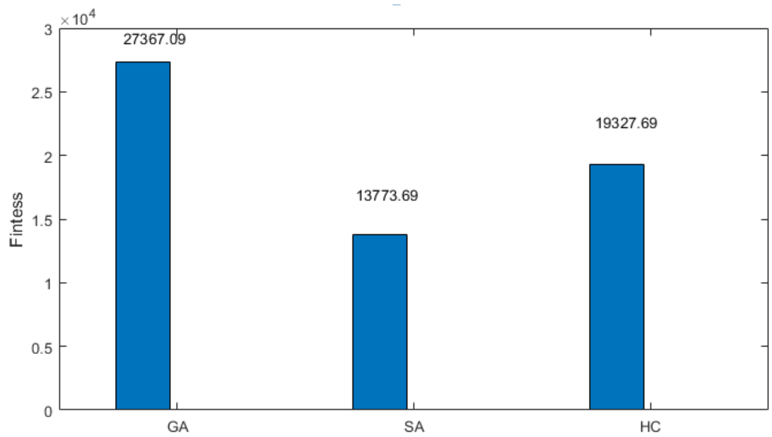


Figure 5.10: Fitness Comparison of algorithms using stopping criteria of maximum of 100 thousand fitness calls

To investigate the efficiency of the algorithms (i.e. their ability to return a good solution in short time), all experiments as described above were repeated using a stopping criteria of 100 thousand maximum fitness calls instead 500 thousand. *Figure 5.10* shows the average fitness performance of all algorithms across the different traffic distributions on the Large problem instance. A very different performance graph is observed compared to when the stopping criteria of 500 thousand maximum fitness calls was used. The Hill climbing algorithm was found to outperform the Genetic algorithm in terms of fitness by approximately 30% while the Simulated annealing returned the most optimal network topologies, outperforming the Hill climber by approximately 29%. However, all algorithms were still found to be effective even under the tight stopping criteria. Figure 5.11 shows the efficiency of the algorithms based on execution time. The Genetic algorithm was found to have the worst efficiency with an average execution time of 4 hours, while the Simulated annealing had an execution time of 1 hour. The Hill climbing algorithm was found to have the highest efficiency for solving the 5G deployment problem with an execution time of 32minutes. The high execution time of Genetic algorithm can be attributed to the extra time it takes to perform the *selection* of parent solutions and crossover (see section 2.2.2.6), while the fast execution time of the Hill climber can be attributed to its simple greedy acceptance criteria, which leads it to converge at a much faster rate. This result suggests that the Hill climbing algorithm may be a good candidate for *on-demand* base station network *management* where finding a good network plan in a timely manner is favoured over finding the most optimal network topology.

Algorithm	GA	SA	HC
Execution time	4.1	1	0.53

Table 5.10: Algorithm execution time in hours

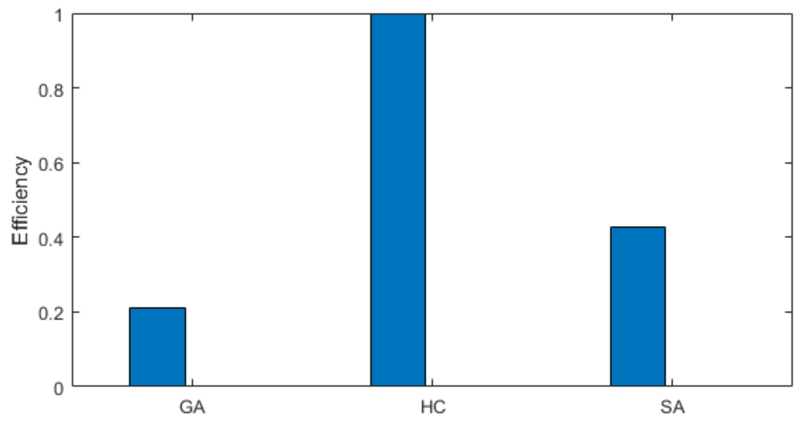


Figure 5.11: Efficiency of algorithms in terms of execution time taken

5.6. Summary

This chapter first provided an optimisation framework for the application of heuristic search for 5G heterogeneous base station deployment, with cell range extension feature, which is a key technology for next-generation 5G mobile networks. The framework which is generic includes an integer programming problem for supporting the design of a cost efficient base station topology that was engineered towards exploiting base station heterogeneity, a solution encoding and fitness function. The performance of three heuristic search algorithms, namely; Simulated annealing (SA), Hill claiming (HC) and Genetic algorithm (GA) were analysed empirically as 5G base station planning algorithms using the proposed framework and a baseline random sampling approach. Each algorithm was run for a maximum of 500,000 and 100,000 fitness calls on two problem instances of different sizes. Experimental results show that the GA and the SA have comparable performance on average in terms of *fitness* of the best found network plan and outperform the HC by up to 50% on some problem instances when the run for up to 500,000 fitness calls. However, the Simulated annealing algorithm is found to outperform the GA across the test instances on average by approximately 50% when executed for only 100,000 fitness calls while the Hill climbing algorithm was found to be the most efficient algorithm in terms of its ability to return a good network in the shortest time compared to the SA and GA, making it the most suitable algorithm for on-demand 5G base station management.

6. Power-aware 2-Phase Incremental Deployment strategy for 5G Deployment

6.1. Introduction

The motivation for this chapter is from the results obtained in the preceding chapter. Despite the effectiveness of the studied heuristics at tackling the 5G network planning problem, a deeper analysis of the designed 5G networks showed that the network power consumption is mainly influenced by the density of macro base stations used in the network topology. For example, a network topology returned by GA algorithm consisted of only 28 macro base stations out of the 239 total base station deployed, yet they accounted for about 92% of the network power consumption and about 45.5% of the CAPEX cost. Hence, this chapter seeks to improve the cost efficiency of the designed networks by proposing a strategy for finding the optimal (i.e. most cost efficient) density of macro base stations in a 5G network design.

This chapter proposes and evaluates a novel power aware two-phase incremental strategy (2-Phase) for resolving the 5G heterogeneous deployment problem formulated in section 5.3 which is independent of the algorithms used for the optimisation. The results from the preceding chapter are used as a benchmarks for evaluating the effectiveness of the strategy. The proposed strategy is to break down the optimisation problem formulated in section 5.3 into two complementary but independent optimisation phases with smaller search spaces (than the original problem), whose solutions are then combined to solve the original problem. The first phase is optimised to maximise coverage cost efficiency and returns a *basic* coverage network based primarily on macro-cell base stations with large coverage footprints. The second phase builds a capacity deployment on the basic coverage network returned by the first phase through the deployment of small-cell base stations that can be switched *on*/*off* in times when the extra capacity is not needed, in order to save power consumption. The proposed strategy is motivated by two concepts; (i) divide and conquer co-operative optimisation, and (ii) small-cell base station *sleep* technology [97], used for minimising network power consumption during off-peak hours.

The divide and conquer technique is an algorithm design paradigm that advocates recursively breaking down a large complex problem into two or more sub-problems of the same or related type, that can be solved with higher optimality [99]. This technique has been applied by a number of authors to other complex optimisation problems with high dimensions and has been shown to improve the solution quality over directly optimising the original optimisation problem, especially on large problem instances.

A key technology for minimising base station network power consumption is the technology to put some base stations to *sleep* during extremely low demand periods (such as at night time in office areas) to save power consumption. Base stations use very little power when *sleep mode* is enabled[6] [15]. Base station *sleep* technology is better suited to small-cell base stations because of their local coverage areas and their ability to be re-activated in a short amount of time, while the technical feasibility of employing *sleep* mode technology in macro-cell base stations has been questioned [97]. Hence we assume that macro base stations will always be active while small-cell base stations can be switched to *sleep* mode during off-peak hours. Based on this assumption, it is a logical hypothesis to make that a network with a high deployment of small-cell base stations and low macro-cell base station deployment will be more power efficient since the small-cells can be switched off when not needed. This hypothesis was observed to hold in the simulation results discussed in section 5.5.3. However, a dense deployment of small-cell base stations may still pose significant CAPEX and power consumption cost. Hence, the strategy seeks the optimal base station density for both macro and small-cell base stations that jointly minimises CAPEX and network power consumption cost.

[6] Note that base station *sleep* mode technology is different from base stations with zero load

The proposed optimisation strategy introduces problem domain intelligence into the exploration of the very large solution search space with the objective of improving the solution quality of the network design on large scale instances and to increase the power efficiency of the returned network. The strategy is generic and can be employed using any combination of algorithms to optimise the phases. For a given scenario, an initial network assessment phase is also used to determine the appropriate optimisation phase to run. Figure 6.1 shows a graphical representation of the strategy.

6.2. Phase 1: Coverage Deployment

In the coverage phase, the meta-heuristic algorithm (or any other suitable algorithm employed) searches for an optimal network purely based on maximising the cost efficiency in terms of the coverage performance metric (see equation 4.6). No consideration is given to the capacity of the network at this stage and the network deployed will form the basic structure of the network that may then be improved upon by the capacity phase, if needed. In the coverage phase, only macro-cell base stations are considered for deployment.

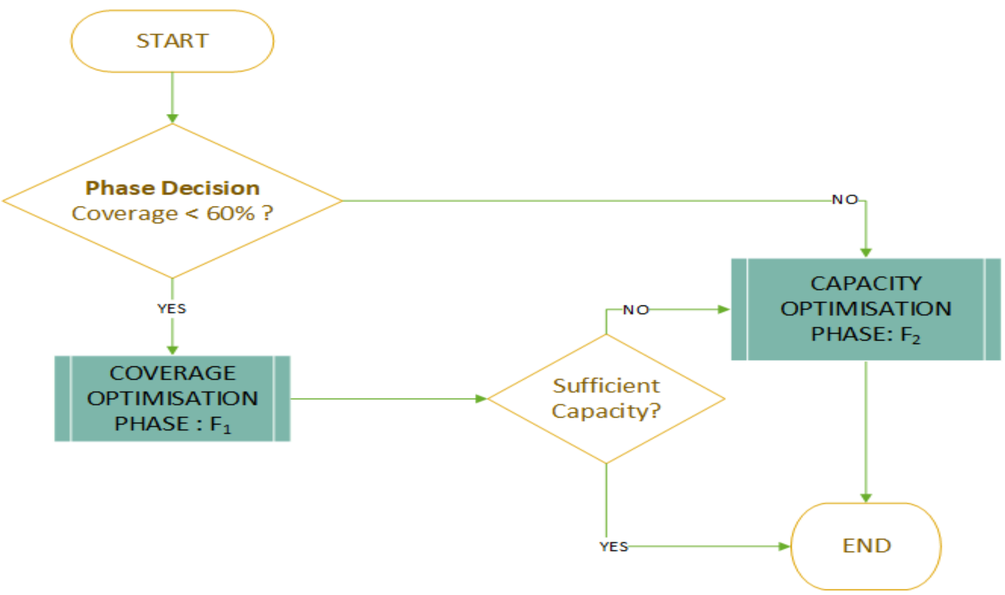


Figure 6.1: Power-aware 2-Phase optimisation for 5G base station deployment (F_1 and F_2 are the fitness functions for the respective phases)

6.2.1. Problem formulation (Phase-1)

Given a set of macro base station candidate site locations, M, the Phase-1 deployment problem is to select a subset of M for the deployment of macro-cell base stations. The transmission power for each deployed macro-cell base station is set to its maximum in order to maximise service area coverage. Let $\boldsymbol{x}$ be a deployment vector with the same length as M such that:

$$x_i = \begin{cases} 1, & \text{if site } i \text{ is deployed with a macro BS } (i \in M) \\ 0, & otherwise \end{cases} \tag{6.1}$$

$$F_1 = \max_{x} : \frac{(equation\ 4.6)^{\alpha}}{cost} \tag{6.2}$$

The optimisation problem defined above replicates the 2G base station planning problem (see section 3.1.2.1). To solve the model a simple binary encoding is used, as in [40]. α is a parameter for tuning the *trade-off* between the achieved service area coverage and deployment cost of macro base stations. Coverage and deployment cost are computed in the same way as in section 4.1.5 and 5.4.1.2, respectively. The objective function (equation 6.2) is simply a weighted cost efficiency function. The objective of this phase is to design a cost efficient coverage network of macro-cell base stations that will then be passed to the capacity deployment phase (i.e. Phase-2) and complemented with small-cell base station deployment.

6.2.2. Results and Discussion (Phase-I)

This sub-section presents results and discussion on the impact of the alpha (α) parameter on the cost efficiency of the deployed network in Phase-I of the proposed strategy. Integer values between 1 and 10 have been analysed for alpha. For simplicity, only the Genetic algorithm (GA) is adopted in this chapter, to evaluate the proposed II-step strategy since both the Genetic algorithm and Simulated annealing were found to have comparable performance in the preceding chapter.

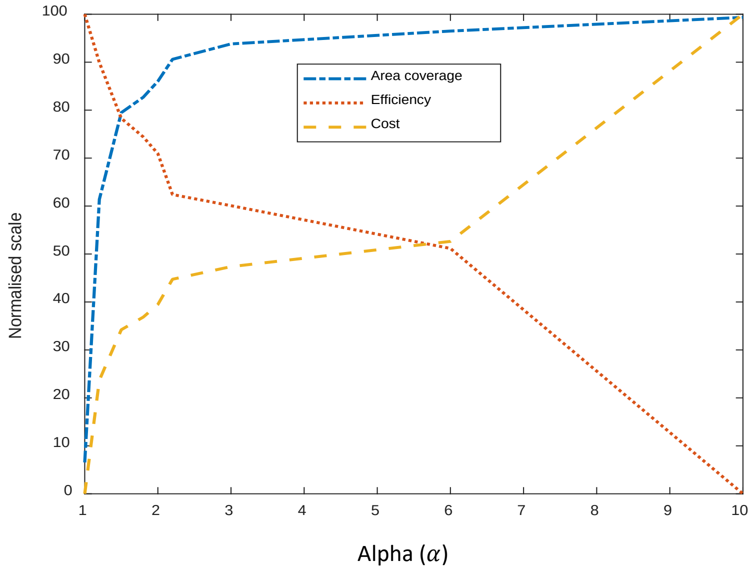


Figure 6.2: trade-off between cost and coverage of macro-cell Base station deployment

Figure 6.2 shows the observed impact of the alpha (α) parameter on the coverage, cost trade-off and the cost efficiency of the optimal macro-cell network returned by the Genetic algorithm. It can be observed that higher values of α increasingly favour the network coverage metric over the cost efficiency of the network in the fitness function. The highest cost efficiency is observed when $\alpha = 1$, however, the returned network does not make practical sense as it achieves less than 10% coverage of the service area (see Figure 6.4, $\alpha =$ 1). To achieve higher network coverage more macro base station nodes are required which in turn increases cost and consequently lowers the cost efficiency of the network. This is mainly because of the expensive infrastructural cost incurred with each additional macro base station deployment and slowing return on coverage due to duplicate coverage as shown in Figure 6.4 (α =10).

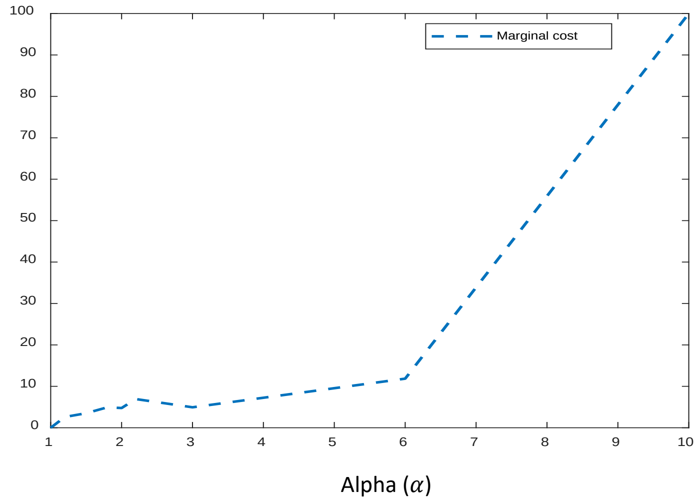
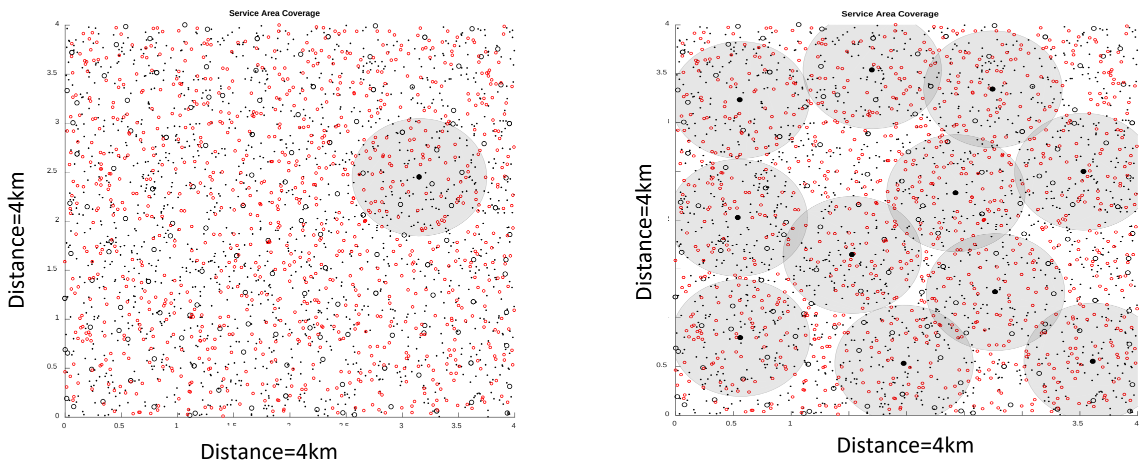


Figure 6.3: Marginal cost of increasing macro-cell Base station deployment

Figure 6.3 shows the marginal cost of coverage as a function of increasing macro-cell deployment. A drastic increase in the marginal cost of coverage (over 800%) of increasing coverage from 90% (α =6) towards 100% by the deployment of additional macro-cell base stations is observed. This result shows the practical point at which the deployment of additional (expensive) macro-cell base station infrastructure to provide additional coverage becomes extremely cost inefficient. Network topologies for different values of alpha (α) are shown in Figure 6.4.



$\alpha = 1$ $\qquad\qquad$ $\alpha = 1.2$

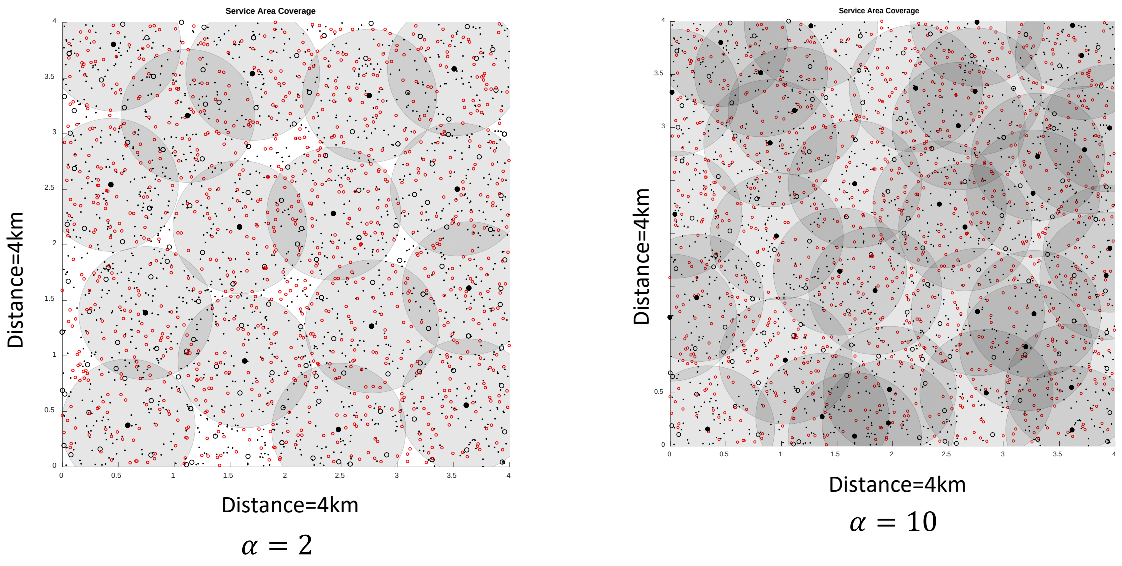


Figure 6.4: Optimal network topologies for different values of alpha (α)

6.3. Phase 2: Capacity Deployment (Small-cell deployment)

The capacity optimisation phase takes the basic structure deployed by the coverage optimisation phase as input and the chosen meta-heuristic tries to improve the capacity and coverage of the basic structure by deploying small-cell base stations, which are more cost-effective than macro-cell base stations. The resulting optimisation problem takes the same form as the 5G problem presented in chapter 5 but with a reduced search space since the macro candidate sites are no longer considered in the optimisation. However, the macro network is included in the computation of the fitness function. The use of small-cell base stations to complement the macro network taking into account the cost efficiency of the macro-cell deployment avoids the deployment of a network with a high density of macro base stations which have expensive infrastructure and are not power aware.

6.4. Evaluation and Discussion on 2-phase Incremental Deployment strategy

This section evaluates the performance of the proposed power-aware two-phase incremental deployment strategy for 5G, using the performance of the Genetic algorithm on the Large problem instance detailed in section 5.5. The proposed strategy is evaluated in terms of its ability to improve the optimal fitness function returned and design a network whose power consumption budget is lowered compared to the results of the Genetic algorithm in the previous chapter.

6.4.1. Experimental setup

Similar to the previous chapter, the performance of the strategy is averaged after 25 independent simulation executions on the Large problem instance (see section 5.5) using the stopping criteria of 500,000 fitness calls. The main characteristic of the Large problem instance is the large search space due to the high density of candidate sites (see Table 5.2). All system parameters are the same as outlined in Table 5.3. The performance of the GA algorithm on the Large problem from section 5.5 is used as a baseline. The strategy is evaluated for different values of the alpha parameter (see 6.2.1) and results are discussed. The Alpha parameter (α) controls the density of macro base stations in the returned network topology and is used in phase-1 of the strategy (see section 6.2).

6.4.2. Evaluations Results

For comparative analysis, all results in this section are presented using a grouped bar chart with a real numbered scale on the *y* axis that indicates performance and the actual units are shown on the *x* axis, for when the strategy is used against when it isn't. The results show the performance of the proposed strategy at *minimising* the power consumption and fitness of the designed 5G networks, using ranging values of the alpha (α) parameter used in equation 6.2 . The aim of the experiment is to find the alpha (α) value at which the strategy performs the best and establish the effectiveness of the proposed strategy. Obviously, the shorter the bars in chart, the better, since 5G network planning is formulated as a *minimisation* problem.

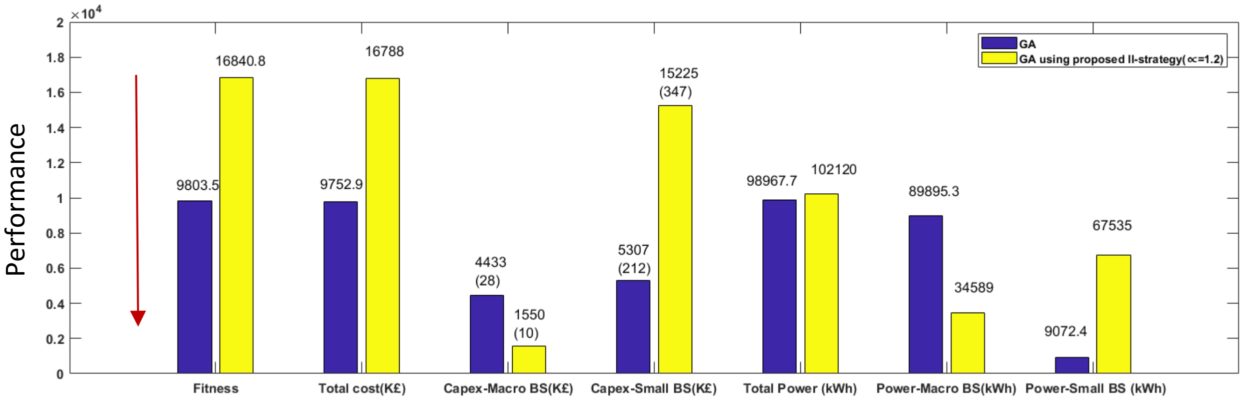


Figure 6.5: Performance of proposed strategy for alpha=1.2 (Uniform traffic distribution)

Figure 6.5 shows the performance of the proposed strategy using a Genetic algorithm for an alpha (α) value of 1.2 based on the uniform distribution traffic instance (section 5.5). The following can be observed; using the proposed strategy with a low value of alpha (i.e. a value close to 1) significantly reduces the number of macro base stations and consequently their CAPEX cost and power consumption relative to the baseline (i.e. when the strategy is not used). Quantitatively, using the strategy with an alpha value of 1.2 reduced the number of deployed macro base stations by almost 65% (from 28 to 10), and results in a 65% and 61% decrease in their CAPEX cost and power consumption, respectively. However, it can be seen that the final network returned when the strategy is used for alpha=1.2 is significantly worse in terms of cost efficiency with approximately 72% higher total cost and about 3% higher power consumption compared to the baseline network. This is explained by the higher cost that is incurred by the denser deployment of small-cell base stations (despite their low individual cost) when the strategy is used for alpha=1.2, deploying a sparse number of macro base stations. The increased density of small-cell base stations deployed when using the strategy for such a low value of alpha is basically to complement the sparse macro base station deployment.

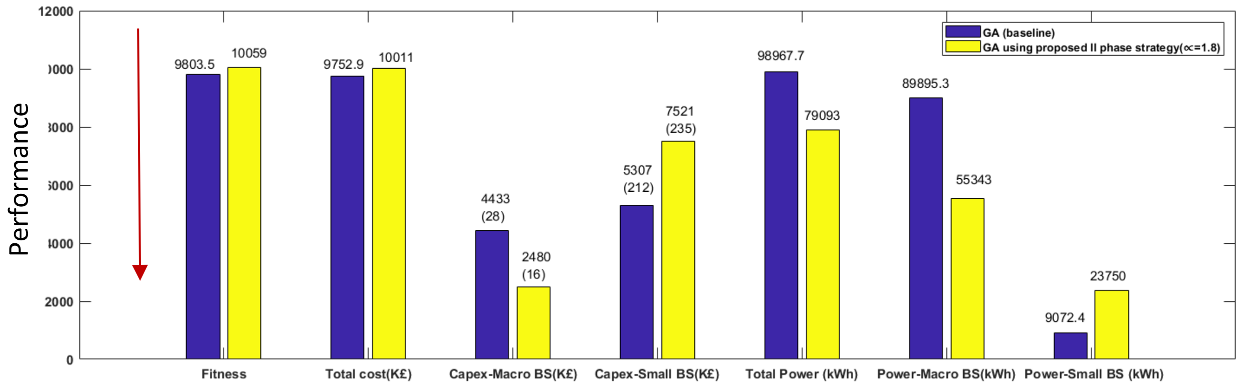
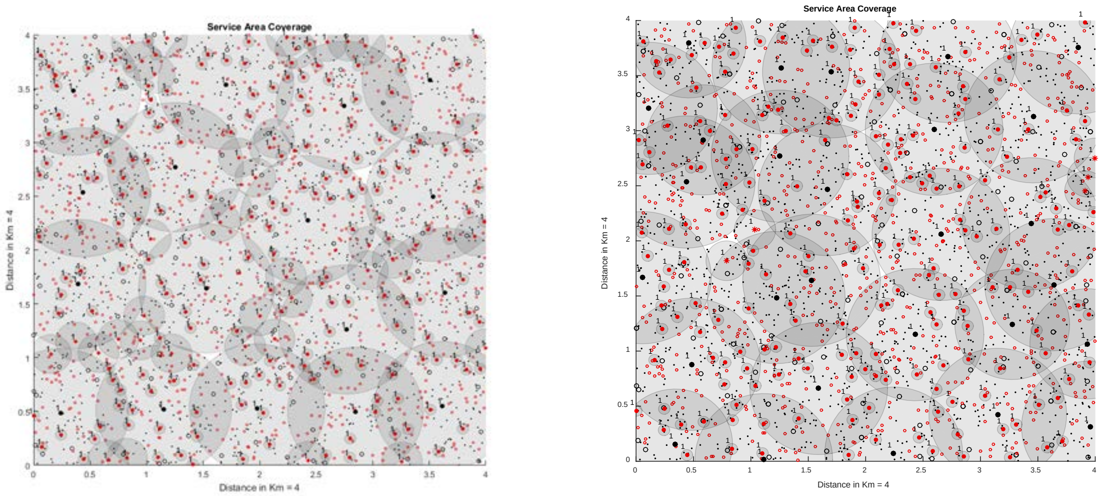


Figure 6.6: Performance of proposed strategy for alpha=1.8 (Uniform traffic distribution)

Figure 6.6 shows the performance of the proposed strategy using a Genetic algorithm for an alpha value of 1.8. It can be observed that the performance of the strategy as measured by the fitness function shows much more comparable performance to the baseline performance compared to the case when alpha=1.2, with only a 2% difference in fitness. A higher value of alpha at 1.8 increased the number of macro base stations deployed from 10 (for alpha=1.2) to 16, which in turn reduced the number of the small-cell base station deployment from 347 to 235. In comparison to the baseline performance, using the proposed strategy resulted in 20% decrease in network power consumption, however, the returned network was slightly worse in terms of total cost (2.6%) for alpha=1.8. The power efficiency gain is mainly from the reduced density of high power consumption macro base stations from 28 in the baseline topology to 16 in the returned network by the proposed strategy as shown in Figure 6.7.



(a) (b)

Figure 6.7: Network topologies. Topology (a) is turned by the proposed strategy while (b) is the baseline topology returned when the strategy is not used. It can be observed that the density of macro base stations is much higher in (b) compared to (a). Macro base stations have high power consumption profiles and should be optimised to create more power-efficient network topologies.

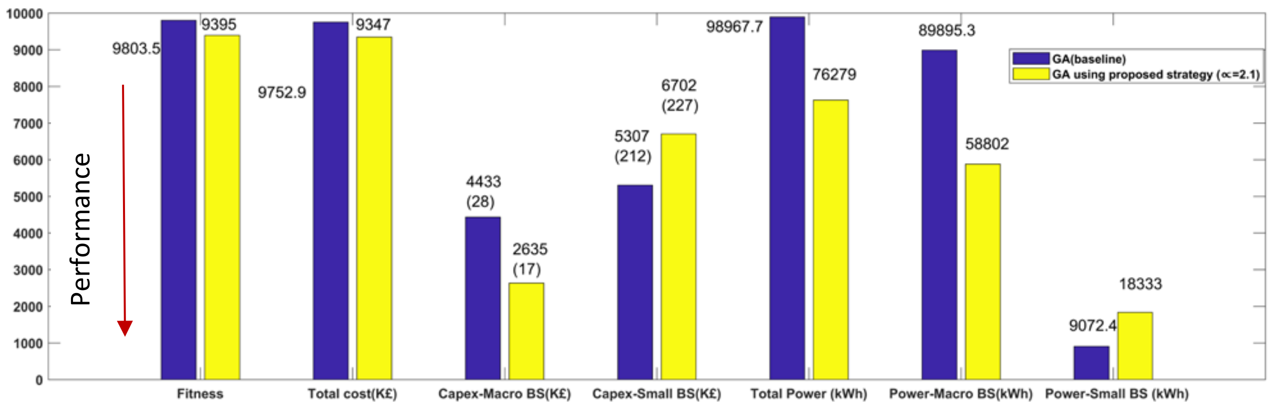


Figure 6.8: Performance of proposed strategy for alpha=2.1 (Uniform demand distribution)

Figure 6.8 shows the average performance of the proposed strategy after 25 runs for an alpha value of 2.1 on the Uniform traffic distribution. It can be observed that the performance of the strategy (as measured by the fitness function) is better than the baseline by 4% on the Uniform traffic distribution. The strategy was found to decrease the network power consumption and total annual cost relative to the baseline performance by approximately 23%

and 4% respectively for alpha=2.1 on the Uniform traffic distribution. A diminishing return on the performance of the strategy relative to the baseline was observed for higher values of alpha. This result shows that for a given traffic scenario, there exist an optimal density of macro base stations that should be complemented with small-cell deployment in designing a heterogeneous base station network that is cost efficient in terms of infrastructural cost and power consumption.

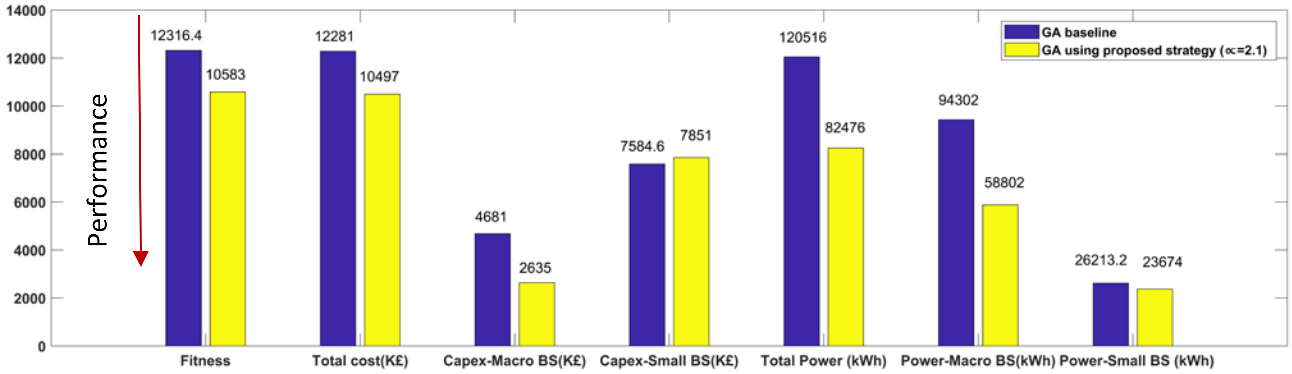


Figure 6.9: Performance of proposed strategy for alpha=2.1 (Gaussian traffic distribution)

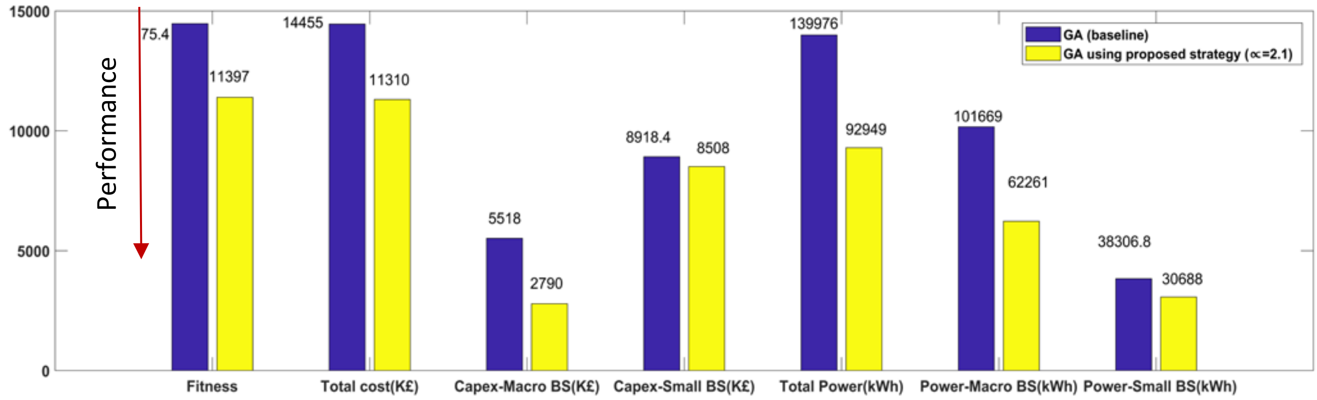


Figure 6.10: Performance of proposed strategy for alpha=2.1 (multi-Gaussian traffic distribution)

Figure 6.9 and Figure 6.10 show the average performance of the proposed strategy after 25 independent simulation runs on the Gaussian and multi-Gaussian traffic distributions, respectively. The strategy returned a network topology with a better fitness by 14% and 27%

(compared to the baseline) and approximately 32% and 34% less power consumption on the Gaussian and multi-Gaussian traffic distributions, respectively.

6.5. Case Study

This section presents results on a case study using the proposed network planning solver outlined thus far. The aim of the case study is to *quantify* the cost-benefit of a heterogonous base station access network architecture over the traditional homogenous macro-cell base station architecture as a function of increasing capacity demand. In the traditional homogenous macro base station architecture, only macro base stations are deployed while in a heterogonous base station network architecture both macro and small-cell base stations can be deployed. The same cost models and assumptions made thus far are sustained. Three traffic demand scenarios are analysed and described below;

I. **Low demand**: The low demand scenario is based on the Uniform traffic distribution. The average throughput requirement for this scenario is set to 1Mbps.

II. **Medium demand**: The medium scenario is based on the Gaussian traffic distribution. The average throughput requirement for this scenario is set to 25Mbps then 50Mbps.

III. **High demand**: The high demand scenario is based on the Gaussian traffic distribution. The average throughput requirement for this scenario is set to 100Mbps.

From Figure 6.11 and Figure 6.12, it is very easy to observe that regardless of the approach used, the power consumption and CAPEX cost increases as the demand for higher capacity increases. This trend is expected as more base stations are deployed to satisfy the increase in demand which in turn increases the CAPEX and power cost required to deploy and operate them. In traditional network planning, only macro BSs are deployed to increase capacity. Macro base stations have large cell sizes but consume significant power in addition to expensive equipment and site acquisition/build up cost. As shown in Figure 6.11 and Figure 6.12, this type of deployment rapidly increases the CAPEX and power consumption cost the network as the demand for capacity rises. In a heterogeneous base station architecture, operators can leverage cheaper small-cell base stations (that consume less power) through the proposed deployment strategy, instead of deploying dense macro base stations, to slow the cost implications of expanding the network. Based on simulation scenarios and taking into account the assumptions made, it is reported that a mobile network operator can save up to 90% on power consumption and 75% on CAPEX by leveraging a heterogeneous base station cellular network over the traditional homogenous macro base station architecture. It is also observed that the cost savings of leveraging a heterogeneous base station access network widen with increasing capacity demand.

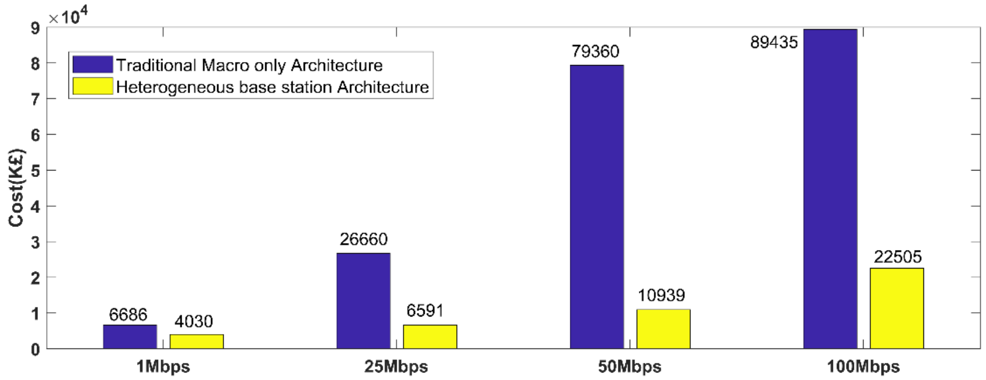


Figure 6.11: CAPEX cost as a function of increasing capacity requirement

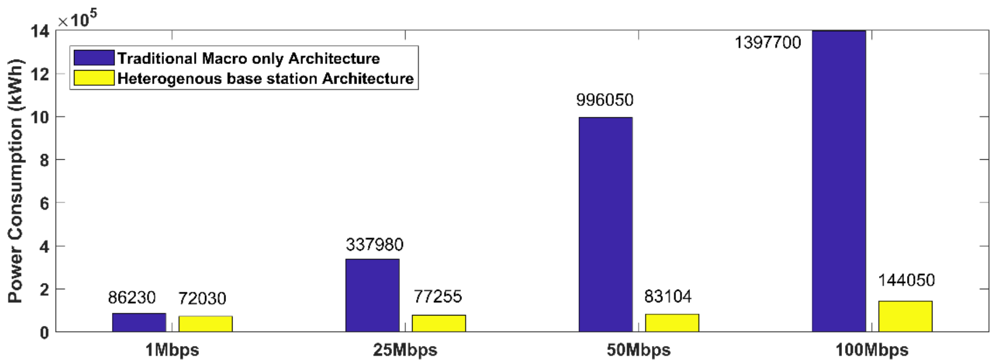


Figure 6.12: Power consumption as a function of increasing capacity requirement

6.6. Summary

This chapter proposed and evaluated a novel power aware two-phase incremental strategy (2-phase) for 5G heterogeneous base station deployment that is independent of the of heuristic search techniques used to optimise the network deployment. The proposed strategy is to break down the 5G base station deployment optimisation problem formulated in section 5.3 in two complementary but independent optimisation problem phases with smaller search spaces (than the original problem), whose solutions are then combined to solve the original problem. The first phase is optimised to maximise coverage cost efficiency and returns a *basic* coverage network using macro-cell base stations with large coverage footprints. The second phase builds a capacity deployment on the basic coverage through the deployment of small-cell base stations. The proposed strategy was evaluated using a Genetic algorithm on a problem instance with 1,178 candidate base station sites and on different demand distributions. The strategy was found to improve the fitness of the Genetic algorithm on average by 4% and decrease the power consumption cost of the returned network by up to 34% depending on the traffic distribution pattern. However, the performance of the strategy is subject to finding the optimal density of macro-cell base stations to be complemented by small-cell deployment by tuning an integer parameter in phase-1.

7. Joint MIMO and Heterogeneous base station 5G access network deployment Model

7.1. Introduction

The previous chapters introduced an optimisation problem for exploiting heterogeneous base station types in the context of cost efficient deployment of next-generation 5G mobile networks and analysed heuristic strategies for optimising it. This chapter builds on the 5G deployment problem formulated in chapter 5.3, to propose and analyse the benefit (in terms of deployment cost efficiency) of an *advanced* 5G base station deployment problem model that jointly optimises heterogeneous base station types and MIMO configurations.

In addition to dense deployment of small-cell base stations in a heterogeneous access network, another key technology for providing high data capacity in 5G is MIMO (Multiple-Input Multiple-Output) spatial multiplexing, which means using multiple antennas on a base station to increase its capacity. Deploying base stations with high MIMO antennas can significantly increase the spectral efficiency since more data bits can be transmitted using the same amount of spectrum, however, this is poised to also increase the power consumption and CAPEX cost of the system [100]. For example, a single transmitter base station system (i.e. no MIMO capability) will definitely cost less to buy than a base station with MIMO capacity. Likewise, a high order MIMO base station will be more expensive and consume more power than a low order MIMO base station since an additional power amplifier is needed to power each additional MIMO transmitter chain. Nevertheless, the use of large-scale MIMO is considered a key technology for meeting the extreme capacity requirement of 5G [19].

Considering the above trade-off, an important research question is *how to maximise the cost efficiency of* MIMO *in 5G?* Existing research to address this question has exclusively focused on the maximising power efficiency by optimising the number of active MIMO chains in low traffic periods also known as *Antenna Muting*, after an initial *un-optimised homogenous* high-order macro-cell MIMO deployment [101][102]. For example, [101] reported after system simulations that antenna muting can reduce the power consumption of a 4x4 MIMO LTE macro-cellular network by up to 50% in a low load scenario without significantly affecting the user throughput. However, a clear mathematical optimisation model was not included. [102] presented a mathematical model for downlink antenna muting in a large-scale LTE MIMO system based on optimising the number of active MIMO RF chains and their transmit powers, and analysed the trade-off between power and spectrum efficiency. However, no clear heuristic algorithms were presented.

Different from existing literature, this chapter proposes and evaluates a *multi-dimensional* approach through an optimisation framework for *jointly* optimising (exploiting) the different configurations of MIMO and heterogeneous base station deployment for more cost efficient 5G base station deployment, since different *configurations* will have different power consumption, CAPEX and system capacity implications. In addition to reducing power consumption of their existing networks in low demand periods, the framework can be used during base station deployment to also minimise infrastructural cost (CAPEX). Hence the main aim of this chapter is to propose and evaluate/quantify the cost efficiency benefit of the framework under the high user data requirement of 5G.

The contributions of this chapter are as follows:

- The formulation of an optimisation framework in which three key 5G technologies; Heterogeneous base station access network, MIMO and small-cell Cell range extension (CRE) are jointly optimised for cost-effective base station deployment. To the best of our knowledge, such a framework for 5G base station deployment has never been explicitly presented before. The work in [103] analysed the energy efficiency of a heterogeneous base station access network with MIMO against other network deployments however their work does not include a clear optimisation framework for jointly optimising heterogeneous base station types, MIMO and small-cell cell range extension (CRE).

- Simulation analysis on the benefit of the *advanced* 5G base station deployment problem framework that *jointly* optimises heterogeneous base station types, MIMO and cell range extension configurations in terms of network deployment cost efficiency.

7.2. System Model

U	Set of demand nodes
M	Set of candidate sites for macro base station deployment
S	Set of candidate sites for small-cell deployment
N	Set of base station *models*
v_i	Site acquisition cost of site $i, i \in M \cup S$
b_i	Backhaul cost of site i
T	Set of MIMO configurations
$e_{(n,t)}$	RF equipment cost of BS *model* n with MIMO configuration t
P	Set of transmission power levels of base stations
D	Set of deployed base stations[7]
N_{TX}	Number of transmitters on base station model n
∂	MIMO efficiency
ρ^u	Signal to interference and noise ratio of UE u
W	Available bandwidth
Cov'	Service area coverage percentage threshold
Cap'	Capacity requirement
B	Set of CRE levels

Table 7.1: System model parameter for joint MIMO and Heterogeneous base station model

The deployment of a 5G mobile network with heterogeneous base station types/models (macro, micro and pico-cells) and MIMO multi-antenna transmission on 3D geographical service area, *A*, is considered. The system model presented here is an extension to section 4.1.1, which did not include MIMO. Each site is defined by 3 variables; (a) *x*,*y*,*z* coordinates

[7] A base station may or may not be deployed with MIMO

(b) site acquisition cost (c) and backhaul cost. The notation x and $\hat{x}$ is used for macro and small-cell base stations respectively, where the distinction is necessary.

7.2.1. Base station Models and Configurations

- In each candidate macro site $m \in M$, it is assumed that operators can deploy an omnidirectional macro-cell base station operating with one of $|T|$ MIMO RF transmitter *chains/configurations*. Let P_t be the signal transmission power of a base station deployed in site m, such that $P_{t(i)} \in P$ is the transmit power of the ith MIMO transmitter of the base station deployed in the site. For simplicity, it is assumed that all MIMO transmitters installed on a base station operate at the same power level. This assumption means that the transmit power of a base station with MIMO can still be controlled by setting a single scaler power variable as done in chapter 5. MIMO base station spatial multiplexing is assumed to increase system capacity [29]. Thus, the capacity of the base station to handle traffic is increased as the number of MIMO RF chains increases, however, this also increases the power consumption of the base station and also the equipment cost.

- While in each small-cell site $s \in S$, one of $|\hat{N}|$ *models* for small-cell base stations can be deployed, operating with one of $|\hat{T}|$ MIMO antenna *configurations* at a transmit power level $P_t \in \hat{P}$, such that $P_{t(i)} \in \hat{P}$ is the transmit power of the ith MIMO transmitter of the base station. Each small-cell BS *model* represents a different *type* of small-cell base station with a different power consumption profile, communication range and infrastructure cost. Small-cell base stations can expand their *coverage* by using *Cell range expansion* (*CRE*) by selecting one of $|B|$ CRE values.

7.2.2. Coverage and Traffic Model

The coverage, traffic and CRE inclusive demand node to base station association model are the same as described in section 4.1.5.1.

$$\Upsilon_{d,c} = \begin{cases} 1 \text{ if point c } (c \in C) \text{ is covered by BS } d \in D \\ 0, otherwise \end{cases} \quad (7.1)$$

$$a_{u,d} = \begin{cases} 1 \text{ if demand node } u \in U \; is \text{ associated to BS } d \in D \\ 0, otherwise \end{cases} \quad (7.2)$$

7.2.3. Network Capacity

The system capacity of the simulated 5G mobile network is computed assuming an LTE-Advanced N_{TX}xN_{RX} MIMO downlink multi-user system. N_{TX} is the number of base station MIMO transmitters and is determined by the installed MIMO *configuration*. While N_{RX} is the number of MIMO antennas at the user equipment. In this project, only the *downlink* is considered i.e. data transfer from the base station to the user equipment. However, conclusions made are expected to also hold for the reverse link.

According to [29], the multi-user MIMO capacity of a base station can be approximately viewed as N_u point to point MIMO links. N_u is the number user equipment served by the serving base station of user *u*. The data capacity of a user equipment *u*, at *sufficiently high* signal to noise ratio (ρ^u), can be approximated by equation 7.3 [29]. ω is the user equipment spectral efficiency for a SISO[8] link computed in equation 4.9. W_u is the bandwidth allocated to a user equipment *u* by the base station. Based on the earlier assumption of an equal resource allocation policy of base stations, W_u is dictated by N_u and the available bandwidth (W) according to equation 7.4.

$$R_u \propto (\min(N_{TX}, N_{RX})\omega)W_u \quad (7.3)$$

$$W_u = \frac{W}{N_u} \quad (7.4)$$

[8] A SISO link is formed by a base station and user equipment with only one antenna.

$$R_u \propto ([1 + \mu\partial]\omega)W_u \tag{7.5}$$

$$\mu = \min(N_{TX}, N_{RX}) - 1 \tag{7.6}$$

$$\partial = \begin{cases} 1, & if\ \rho^u \geq 12\text{dB} \\ 0.6, & 5 \leq \rho^u < 12\text{dB} \\ 0.3, & \text{otherwise} \end{cases} \tag{7.7}$$

$$AV = \frac{\sum_u^{|U|} R_u}{|U|} \tag{7.8}$$

However, the spatial multiplexing *gain* (μ) of MIMO drops significantly at lower signal to noise ratio values [104]. To model this effect, a MIMO efficiency curve fitting parameter, ∂, is introduced at lower UE signal to noise ratio values. Hence, equation 7.3 is modified to equation 7.5. The network capacity, measured by the average user network throughput is then given by equation 7.8.

7.3. Problem Formulation

The objective of the *advanced* 5G base station deployment problem is to *jointly* find the optimal number, locations, types, transmission powers, small-cell CRE *bias* vector and MIMO configurations of base stations that minimises the CAPEX and power consumption network cost, subject to the *coverage* and *capacity* constraint. All notations used here are defined in Table 7.1. The following decision variables are introduced for the advanced 5G base station deployment problem;

$$x_i = \begin{cases} 1, & \text{if a BS is deployed in site } i \in M \cup S \\ 0, & otherwise \end{cases} \tag{7.9}$$

$$z_{in} = \begin{cases} 1, & \text{if a BS model } n \in N \text{ is deployed in site } i \in M \cup S \\ 0, & otherwise \end{cases} \tag{7.10}$$

$$j_{pd} = \begin{cases} 1, & \text{if a BS } d \text{ uses power level } p \in P \text{ }, d \in D \\ 0, & otherwise \end{cases} \quad (7.11)$$

$$k_{bd} = \begin{cases} 1, & \text{if a small BS } d \text{ uses bias level } b, b \in B \text{ }, d \in D \\ 0, & otherwises \end{cases} \quad (7.12)$$

$$f_{nt} = \begin{cases} 1, & \text{if a BS model } n \in N \text{ is deployed with MIMO config } t \in T \\ 0, & otherwise \end{cases} \quad (7.13)$$

The 5G network design objectives are as follows:

$$\mathrm{C1} = \sum_{m \in M}^{|M|} x_m \sum_{n \in N}^{|N|} z_{mn} \sum_{t \in T}^{|T|} f_{nt} \left(e_{(n,t)} + (v_m + b_s) \right) \quad (7.14)$$

$$\mathrm{C2} = \sum_{s \in S}^{|S|} x_s \sum_{n \in \hat{N}}^{|\hat{N}|} z_{sn} \sum_{t \in \hat{T}}^{|\hat{T}|} f_{nt} \left(e_{(n,t)} + (v_s + b_s) \right) \quad (7.15)$$

CAPEX: $\min_{\boldsymbol{x},\boldsymbol{z}} \ [\mathrm{C1} + \mathrm{C2}]$ (7.16)

$$\mathrm{P1} = \sum_{s \in S}^{|S|} x_s \sum_{n}^{|\hat{N}|} z_{sn} \sum_{t}^{|\hat{T}|} f_{nt} \sum_{p}^{|\hat{P}|} j_{pd} \, PC(n,p,t) \quad (7.17)$$

$$\mathrm{P2} = \sum_{m}^{|M|} x_m \sum_{n}^{|N|} z_{mn} \sum_{t}^{|T|} f_{nt} \sum_{p}^{|P|} j_{pd} \, PC(n,p,t) \quad (7.18)$$

Power: $\min_{\boldsymbol{x},\boldsymbol{j},\boldsymbol{z},\boldsymbol{k}} \mathrm{P1} + \mathrm{P2}$ (7.19)

Subject to

$$\left(\sum_{d=1}^{|D|} \sum_{c=1}^{|C|} \Upsilon_{dc} \right) \geq Cov' \quad (7.20)$$

$$\sum_{t=1}^{|T|} f_{nt} \leq 1 \; \forall n \in D \tag{7.21}$$

$$AV \leq Cap' \tag{7.22}$$

The above optimisation problem designs a high capacity but cost efficient base station access network by *jointly* exploiting heterogeneous base station types, MIMO multi-antenna transmission and cell range extension technology. The optimisation problem extends the problem defined in section 5.3 by the introduction of a new dimension, which is to also optimise the MIMO configuration per deployed base station. In the *advanced* 5G problem formulation, a base station's capacity, power consumption and equipment cost are a function of the MIMO *configuration* it uses.

Identical to section 5.3, equation 7.20 and 7.22 ensure that the coverage and capacity requirements are meet as hard constraints. While equation 7.21 is a new constraint that states that a deployed base station can only use one MIMO *configuration*. The *advanced* 5G problem formulation inherits all other constraints defined in section 5.3 and as such, they are not redefined here.

7.4. Optimisation

In order to optimise the *advanced* 5G problem formulation, the procedures outlined in chapter 5 and 6 are adopted. However, the solution encoding is extended to incorporate the extra dimension of MIMO optimisation. The solution encoding presented in section 5.4.1.1 is extended by the introduction of an additional column to the candidate site configuration matrix to hold the MIMO *configuration* for each deployed site, as illustrated in Figure 7.1. The decoding mechanism is the same as presented in section 5.4.1.1.

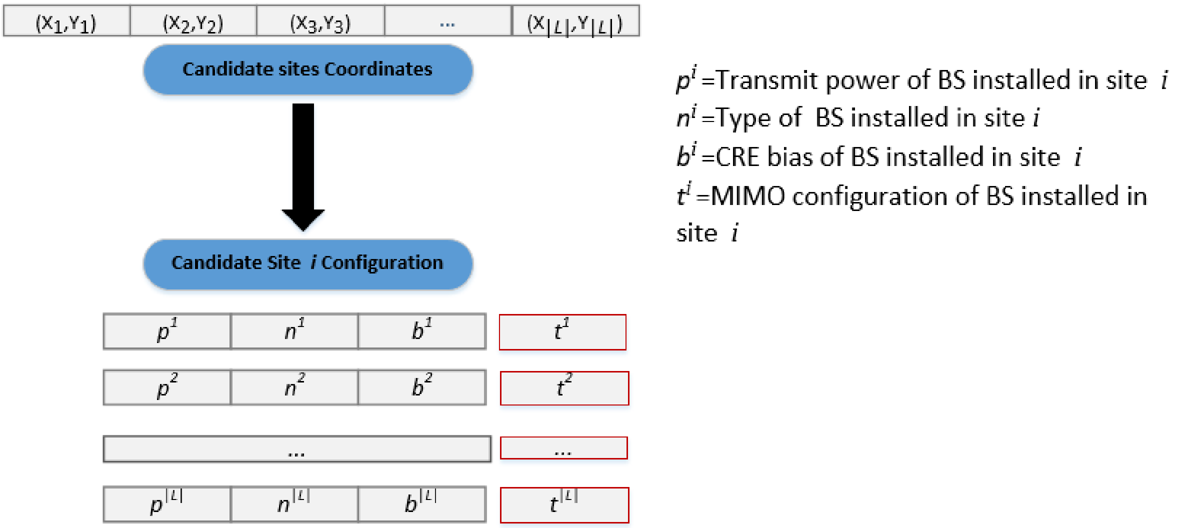


Figure 7.1: Illustration of solution encoding for *advanced* 5G network planning with MIMO

7.5. Results and Discussion

This section evaluates the proposed *advanced* 5G base station planning problem that *jointly* optimises the base station types to deploy, their MIMO *configurations* and cell range extension, in terms of the network deployment cost efficiency and discusses results observed. It is necessary to distinguish between network deployment and power consumption efficiency. The deployment cost looks at the *total cost* of the network design which includes both CAPEX and power consumption. While power consumption cost exclusively focuses on the power usage of the network.

7.5.1. Simulation set up

8. **Parameter**	**Values**		
Frequency	1.8 GHz		
Macro/small BS height	31m / 5m		
Coverage req.	-110dBm		
Bandwidth /tier	50Mhz		
K_1	1		
K_2	20000		
ϵ	1		
Demand distribution	Normal		
Base station Types	**Macro BS**	**Micro BS**	**Pico BS**
Max. Cell radius (Km)	0.6	0.18	0.05
Max. Power (dBm)	46	38	22
Power levels (dBm)/ Transmitter	46,43,40	38	22
Antenna Gain dB	18	6	6
CRE config. (dBm)	NA	0,1,2,3,4,5	0,1,2,3,4,5
Equipment Cost of SISO BS (£)	40,000	0.3* Macro BS	0.1* Macro BS
Site Cost (£)	100,000	0.3* Macro BS	0.05*MacroBS
Backhaul (£)	15000	15000	15000
Energy unit price (£), η	0.13		
MIMO config	1x1 to 8x8		
Algorithm	Genetic algorithm		

Table 7.2: Simulation Parameters

The following system parameters are used in the results presented hereafter. All base stations are assumed to use omnidirectional antennas. It is assumed that macro and small-cell base stations use separate 50MHz bandwidth at 1.8GHz frequency range as such no *inter-tier* interference is assumed between them, however, there is *inter-cell* interference between cells of the same tier since they are co-channel. Other interference scenarios can also be assumed. When only macro-cell base stations are used, the entire 100Mhz bandwidth is available to them. Table 7.2 shows all the system parameters assumed. The network *cost* and power consumption are computed in the same manner as described in 5.4.1.2 and 4.1.5.3 respectively, assuming a period of 1 year. However, to capture the inherent equipment cost difference between (for example) a base station with a single transmitter (SISO BS) and a

MIMO base station, it is assumed that the equipment cost of a MIMO base station is 20% (of the equipment cost of a SISO BS) higher for each additional MIMO RF chain [105]. For example, a three (3) transmitter MIMO base station, will cost £64,000 ($(3 \text{ x } 0.2 \text{ x } costSISO\ BS) + costSISO\ BS$) instead of £40,000 for a single transmitter base station (SISO BS). The equipment cost values used are based on domain expert recommendation and the literature. All simulations are repeated 25 times and the best run is reported. The scenario 'setup' is the MIMO *configuration* used. It is assumed that N_{TX} =N_{RX}

8.1.1. Case study

To quantify the cost efficiency benefit of the proposed *advanced* 5G base station deployment framework, the deployment framework is analysed as against the following *single* dimensional deployments from the literature;

A. **Macro BS + MIMO:** This deployment model uses only macro-cell base stations and relies on homogenously increasing BS MIMO setup to deliver the required UE throughput level [101].

B. **HetNet**: This deployment model exploits base station heterogeneity and relies on the deployment of small-cell base stations to provide the required throughput but does not include MIMO capability and CRE [87].

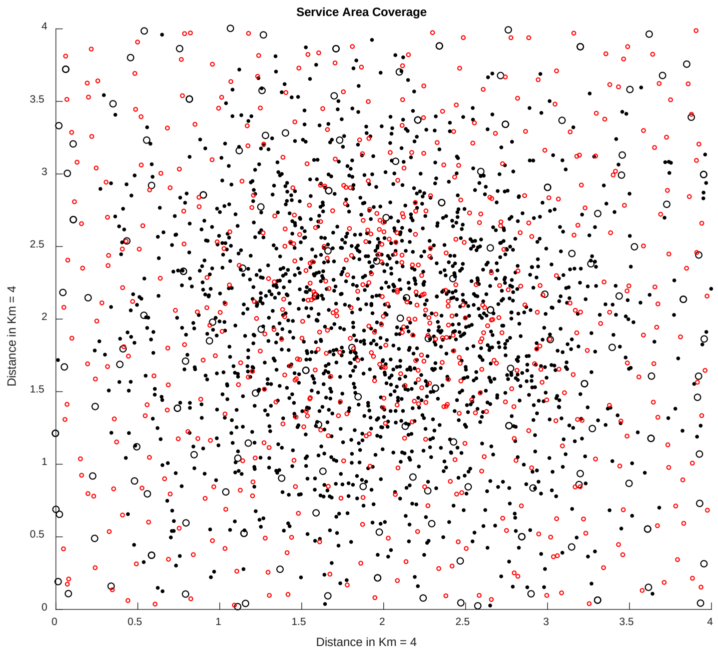


Figure 7.2: Simulation Case study service area. Black circles are candidate sites for macro-cell base stations, red circles are candidate sites for small-cell base stations. Black dots are the demand nodes.

The proposed *advanced* 5G base station deployment model *jointly* exploits heterogeneity in three key 5G technologies, heterogeneous base station architecture, MIMO and small-cell range extension by *jointly* optimising their respective *configurations*.

The 5G network deployment case study considered is a 16Km^2 service area with 778 candidate sites for base station location and 2000 demand nodes normally distributed as shown in Figure 7.2. The 5G network capacity requirement is first set to 50Mbs then increased to 350Mbps.

Dep	MIMO	Cov	DC(M£)	DE	#Mac	#BSs	PC(kWh)
A(baseline)	1x1	100	28.26	1.8	182	182	396267
A	2x2	99	16.53	3.0	101	101	491962
A	3x3	100	12.5	4.0	72	72	542966
A	4x4	100	10.95	4.6	59	59	704338
A	5x5	100	10.59	4.7	53	53	791085
A	6x6	100	10.19	4.9	47	47	838579
A	7x7	100	10.68	4.7	45	45	977568
A	8x8	100	9.95	5.0	38	38	1018311

Table 7.3: Comparison of deployment cost efficient as a function of the MIMO configuration for an average network user rate of 50Mbps. (PC: Power consumption, DC: Deployment cost, Dep: Deployment, #Mac: number of macro BSs, Cov: Coverage)

Table 7.3 shows the influence of MIMO on the network deployment cost efficiency for achieving an average network user rate of 50Mbps using Deployment **A**, which utilises only macro-cell base stations. It can be clearly observed from Table 7.3 that increasing the MIMO setup (i.e. the number of MIMO transmitters) across the base stations consistently results in an increase in the network deployment cost efficiency. Compared to the baseline with no MIMO, the network deployment cost efficiency increased by approximately 178% when the MIMO configuration per base station is increased to 8x8. As shown in Table 7.3, a main characteristic of the network returned when the MIMO configuration per base station is increased to 8x8, is the very low number of base station sites deployed (79% less) compared to the baseline when MIMO is not used. When high order MIMO is used on a base station, the capacity of the base station is increased and consequently, the number of user equipment it can serve is also increased. This means that a reduced number of base stations can be used to provide the same quality of service when the base stations use high order MIMO configurations. This leads to significant network deployment cost savings that arise from the reduced cost associated with the deployment of new base station sites and backhauling them to the core network. However, despite the significant reduction in the number of base station sites required when the MIMO configuration per base station is increased to 8x8, this deployment configuration was observed to consume the highest amount of power. Compared to the baseline with no MIMO, the network power consumption increased by approximately 157% when the MIMO configuration per base station is increased to 8x8. The increase in power consumption is mainly a consequence of the extra power amplifiers that are required to power each extra MIMO transmitter.

Deployment	MIMO	Cov	DC(M£)	DE	#Mac	#Mic	#Pic	#BS	PC(kWh)
A (Macro+MIMO)	8x8	100	9.95	5.0	38	0	0	38	1018311
B (HetNet)	1x1	98	17.95	2.8	17	219	117	353	242013
Proposed (HetNet+MIMO+CRE)	All	100	8.41	6.0	17	78	25	120	197096

Table 7.4: Comparison of 5G deployment models (for 50Mbs average network user throughput)

Table 7.4 presents a comparison of the proposed *advanced* 5G base station deployment framework that *jointly* exploits three key 5G technologies (heterogeneous base stations, MIMO and CRE) against two existing *one-dimensional* models from the literature, in terms of network deployment efficiency. Deployment **A**, which utilises macro-cell base stations installed with a high order MIMO configuration was observed to be more cost efficient than Deployment **B (**which exploits small-cells but not MIMO**)** by approximately 78%. The main difference in their respective network topologies can be seen in the number of base station sites. While a high order MIMO macro-cell deployment (Deployment **A**) requires only 38 candidate sites (out of the 778) to be installed, Deployment **B**, which relies on the deployment of small-cell base stations installs as many as 315 more sites, to provide the same average user throughput of 50Mbps. However, it can be seen that Deployment **B** which relies on dense small-cell deployment rather than high order MIMO macro-cell deployment (Deployment **A)**, is more power efficient by approximately 320%. The proposed *advanced* 5G base station deployment framework can be seen to be the most cost efficient deployment, improving the network deployment cost efficiency by 20% and the power efficiency by approximately 23%. These cost efficient gains can be attributed to the *increased network design flexibility* introduced by the proposed framework in terms of possible network *configurations* by leveraging both MIMO and small-cell deployment as well as cell range extension. Figure 7.3 illustrates the heterogeneous configuration network design returned by the *advanced* 5G base station deployment framework. However, the framework also increases the size of the problem search space due to an increase in the number of network *configuration possibilities.*

Deployment	MIMO	Cov	DC(M£)	DE	#Mac	#Mic	#Pic	#BS	PC(kWh)
A (Macro+MIMO)	8x8	100	47.41	7.4	182	0	0	182	3051658
B (HetNet)	1x1	-	-	-	-	-	-	-	-
Proposed (HetNet+MIMO+CRE)	All	100	20.34	17.2	17	164	108	289	197096

Table 7.5: Comparison of 5G deployment models (for 350Mbs average network user throughput)

A second empirical simulation is performed using a much higher capacity requirement of 350Mbps average network user throughput instead of 50Mbps, and results are shown in Table 7.5. As shown in Table 7.5, Deployment **B,** which relies on the dense deployment of small-cell base stations was unable to meet the much-increased capacity requirement of 350Mbps and as such is not included in the results for fairness. This was mainly due to the effect of *inter-cell interference* between small-cells as their density is increased. This demonstrates that interference mitigation techniques will be key to achieving the high capacity requirement of 5G. As expected, the network deployment cost, power consumption and the number of base stations deployed increases sizably compared to results in Table 7.4 (when the capacity requirement was 50Mbps), regardless of the deployment model. This is logical as more network infrastructure is required to meet the raised capacity requirement. However, the proposed *advanced* 5G deployment model can be seen to maximise the network deployment cost and power efficiency by approximately 133% and 1448% (respectively) compared to

Deployment **A,** despite installing more candidate sites. The deployment cost and power saving gains are achieved by balancing the use of MIMO and small-cell deployment such that cost is minimised. These results demonstrate the deployment cost gains introduced by the proposed *advanced* 5G base station deployment model that exploits heterogeneity in all three technologies by deciding if it is more cost effective to deploy a new base station, the type of base station or if it better to employ more MIMO antennas on existing base stations.

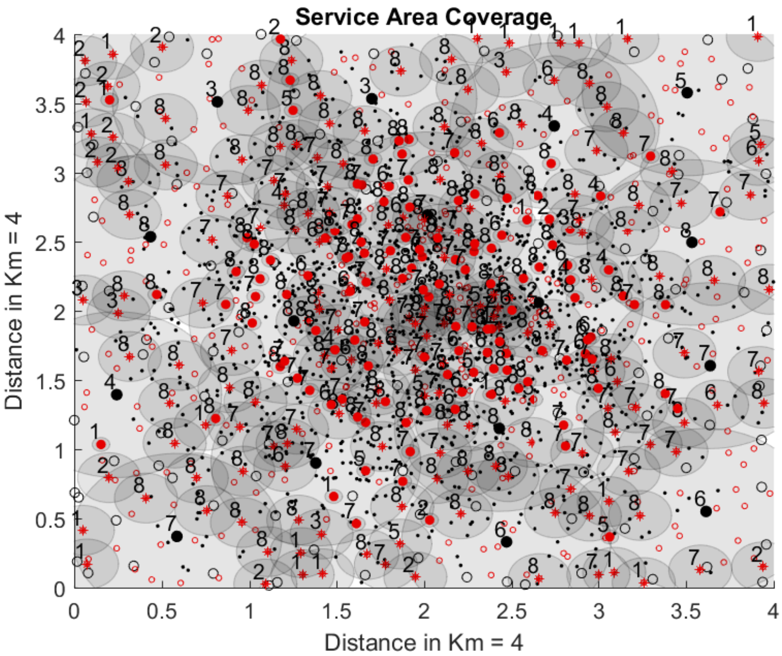


Figure 7.3: Network topology created by the advanced 5G base station deployment framework. The numbers indicate the number of MIMO transmitters installed on a base station. It can be seen that the MIMO setup per base station is different as well as the types of base stations deployed. Bold black dots are installed macro BS locations while bold red dots/stars are installed pico/micro base stations.

8.2. Summary

This chapter presented and evaluated an *advanced* 5G base station deployment framework in which three key 5G technologies; heterogeneous base station architecture, MIMO and small-cell range extension configurations are jointly optimised for more cost efficient base station deployment. This is in contrast to existing base station deployment models from the literature that take a *one-dimensional* approach focused on only one technology. The framework includes an enabling integer programming problem and a solution encoding for applying meta-heuristics and is presented as an extension to chapter 5. The benefit of the *advanced* 5G base station deployment framework (in terms of network deployment cost efficiency) was analysed against two deployment models from the literature: (i) high order MIMO macro-cell network deployment and (ii) high-density heterogeneous base station network deployment, through empirical simulations. Simulation results show that the *advanced* 5G base station deployment framework can improve the network deployment cost and power efficiency by more than 100% and 1000% (respectively) when the capacity requirement is high, compared to a high order MIMO macro-cell network. Other results show that the capacity gain from the dense deployment of small-cell base stations is limited by inter-cell interference. Furthermore, results show that there is a sizable reduction in the number of deployed candidate sites required to provide the same level capacity when higher MIMO order base stations are deployed.

9. Conclusion and Future work

The sustained growth in the number of mobile user devices driven by the introduction of data services, the take-off of the internet and smart user equipment, and the aggressive forecast by industry experts has continued to push the data transfer capacity requirement on mobile networks and has motivated research into the design of 5th generation (5G) mobile networks. A key concern in the design of 5G is the infrastructure and power consumption cost of the base station network, which is expected to be significantly more advanced and dense than of existing conventional mobile networks. For example, unlike conventional mobile standards, which are based on *flat homogenous* base station access network architecture, 5G is to be designed based on a dense *multi-tier heterogeneous* base station access network with *small-cell* base stations and employing advanced technologies like higher order signal spatial multiplexing (MIMO) and cell range extension. *Optimising* the design deployment of 5G base station network is an important challenge faced by mobile network operators in order to provide the very high data transfer speed requirement of 5G at minimum infrastructure and power consumption cost. However, the complex 5G base station network environment requires the development of novel strategies for base station network design and motivates the research work presented in this thesis.

This thesis presented a core optimisation framework for the cost efficient design of 5G base station networks, based on the application of meta-heuristic/heuristic algorithms. It provides novel first steps into the design of 5G mobile networks using heuristic search. The main methodology adopted is the use of mathematical programming models and empirical system level simulations. The following key contributions have been made:

1. The proposal of integer programming models for supporting the decisions on the deployment of an optimal base station topology in a 5G mobile network, in order to

find the best trade-off between providing the ‘*high capacity everywhere*’ requirement of 5G and minimising system cost. The proposed network design integer programming models have been designed to *exploit* configuration *heterogeneity* offered by three key 5G technologies; heterogeneous base station architecture, MIMO and cell range extension configurations for more cost efficient base station network design.

2. The second contribution is the definition of a clear framework for the application of iterative fitness based heuristic search techniques such as *meta-heuristics* for planning 5G mobile networks. The framework includes a solution encoding, fitness function and definition of search operators. Using the framework, the performance of three heuristic search techniques, namely; Genetic algorithm, Simulated annealing and Hill climbing are analysed as deployment algorithms for 5G.

3. The third contribution is the proposal of an independent power consumption aware strategy for planning 5G base station network, based on the principle of *divide and conquer co-operative optimisation*. Empirical simulation results validate that the proposed base station planning strategy is able to save as much as 34% of overall network power consumption depending on the traffic demand scenario.

9.1. Results

This section is an overview of the main contribution chapters and their results.

Chapter 5 presented an optimisation framework for the application of iterative fitness based heuristic search to the deployment of 5G heterogeneous base station architecture with cell range extension technology. The framework has three components: an integer programming 5G base station deployment challenge, which is designed towards exploiting base station heterogeneity for cost efficient base station deployment; a solution encoding, and a fitness function. The performance of three meta-heuristics algorithms; Simulated annealing, Hill climbing and Genetic algorithm were analysed as base station deployment tools for 5G in terms of optimality and efficiency. Each algorithm was run for a maximum of 500,000 and 100,000 fitness calls on two problem instances of different sizes. Experimental results show that the GA and the SA have comparable performance on average in terms of *fitness* of the best found network plan and outperform the HC by up to 50% on some problem instances when the run for up to 500,000 fitness calls. However, the Simulated annealing algorithm is found to outperform the GA across the test instances on average by approximately 50% when executed for only 100,000 fitness calls while the Hill climbing algorithm was found to be the most *efficient* algorithm in terms of its ability to return a *good* network in the shortest time compared to the SA and GA, making it the most suitable algorithm for on-demand 5G base station *management*.

Chapter 6 proposed and evaluated a power-aware 2-Phase incremental strategy (based on the 5G base station deployment problem formulated in **chapter 5)** that is independent of the meta-heuristic algorithm used as the optimisation tool. The proposed strategy is to break down the 5G base station deployment optimisation problem formulated in **Chapter 5** in two complementary but independent optimisation problem phases with smaller search spaces (than the original problem), whose solutions are then combined to solve the original problem. The first phase is optimised to maximise coverage cost efficiency and returns a *basic* coverage network using only macro-cell base stations with large coverage footprints. The second phase builds a capacity deployment on the basic coverage through the deployment of small-cell base stations. The strategy is evaluated by comparing the average fitness and the network cost of the returned network topology when the strategy is used against when it is not. The proposed strategy was evaluated using a Genetic algorithm on a problem instance with 1,178 candidate base station sites and on different traffic demand distributions. The strategy was found to improve the fitness of the Genetic algorithm on average by 4% and decrease the power consumption cost of the returned network by up to 34% depending on the traffic distribution pattern. However, the performance of the strategy is subject to finding the optimal density of macro-cell base stations to be complemented by small-cell deployment by tuning an *alpha* parameter. A case study analysis using the proposed network planning solver was performed to *quantify* the cost-benefit of a heterogonous base station access network architecture over the traditional homogenous macro-cell base station architecture as a function of increasing capacity demand. The case study results show that a mobile network operator can save up to 90% on power consumption and 75% on CAPEX by leveraging a heterogeneous base station access network with small-cells over the traditional homogenous macro base station architecture. It is also observed that the cost savings of leveraging a heterogeneous base station access network widen with increasing capacity demand.

Chapter 7 extended the 5G deployment challenge in **chapter 5**, to propose and analyse the benefit of an *advanced* 5G base station deployment problem framework that *jointly* optimises heterogeneous base station types, MIMO and cell range extension configurations for achieving cost efficient and high capacity base station deployment. The framework includes an enabling integer programming problem and solution encoding for applying heuristic techniques and is presented as an extension to **chapter 5**. The benefit of the *advanced* 5G base station deployment framework (in terms of network deployment cost efficiency) was analysed against two deployment models from the literature: (i) high order MIMO macro-cell network deployment and (ii) high-density heterogeneous base station network deployment, through empirical system level simulations. Simulation results show that the *advanced* 5G base station deployment framework can improve the network deployment cost and power efficiency by more than 100% and 1000% (respectively) when the capacity requirement is high, compared to high order MIMO macro-cell network. Other results show that the capacity gain from the dense deployment of small-cell base stations is limited by inter-cell interference. Furthermore, results show that there is a sizable reduction in the number of deployed candidate sites required to provide the same level capacity when higher MIMO order base stations are deployed.

9.2. Limitations

The main limitation of this thesis is the lack of data from mobile network. Such data which is considered commercially sensitive by most mobile networks would have been useful to produce tighter bounds on the results. Nevertheless, the simulated data used to analyse the strategies have been developed in close collaboration with some industry experts and with extensive research of the existing references.

9.3. Future Work

This section looks at the possible extensions to the work presented in this thesis. The possible extensions are discussed from three perspectives; system modelling, algorithms and scenarios.

9.3.1. System Modelling

The conclusions made in this thesis have been based on a preliminary system model for deployment analysis of 5G cellular networks with heterogeneous base stations based on the 4G LTE-Advanced cellular downlink standard. One direction to extend the work is to employ more intrinsic modelling. For example, ray tracing algorithms could be used to more accurately model signal propagation between a base station and user equipment instead of empirical models. Another improvement of the work would be to explicitly consider the *uplink* as well as the *downlink* direction in the system model. Furthermore, a more detailed resource allocation policy could be included into how base stations share their transmission resources to active user equipment instead of the equal resource allocation policy used in this thesis. Further, the assumption that all base stations use omnidirectional antenna can be extended to include the use of directional antennas and beamforming when MIMO is used.

9.3.2. Algorithms

The work presented in this thesis only analysed the performance of three meta-heuristics; the Genetic algorithm, the Simulated annealing and the greedy Hill climbing algorithm. A natural extension of the work is to analyse the performance of other meta-heuristic algorithms such Particle swarm optimiser, Ant colony algorithm or even hybrid algorithms. Furthermore, the work presented in this thesis only utilised stochastic search variation operators, it will be useful and interesting to look at the possibility of developing intelligent problem specific search operators.

9.3.3. Scenarios

The 5G mobile network analyses presented in this thesis has focused on the single operator non-sharing greenfield base station deployment taking into account three key 5G technologies; heterogeneous access network, MIMO spatial multiplexing and cell range extension. A very interesting improvement of this thesis would be to consider the potential cost saving implication of network infrastructural sharing between different mobile networks in the developed deployment models. Furthermore, other 5G technologies like carrier aggregation and indoor femto-cell networks could be considered for future work. Another very interesting angle for future work is to consider the environment impact of 5G base stations in terms of electromagnetic field radiation.

A. Appendix

This appendix provides additional details about the system model presented in Chapter 4.

Okumura-Hata model

This section describes in detail the Okumura-Hata signal propagation model used to compute the signal path-loss (PL) between a base station and a demand point, in equation 4.1.

$$PL = A + B\ log(d) + C \tag{A.1}$$

where A, B, and C are factors that depend on frequency and antenna height.

$$A = 69.55 + 26.16 \log(f_c) - 13.82 \log(h_b) - a(h_m) \tag{A.2}$$

$$\mathrm{B} = 44.9 - 6.55 \log(h_b) \tag{A.3}$$

where f_c is the frequency given in MHz and d is the distance between the base station and the user equipment in km. h_b and h_m are the base station and user equipment heights respectively in meters.

The function $a(h_m)$ and the factor C depend on the environment:

- small and medium-sized cities:

$$a(h_m) = (1.1 \log(f_c) - 0.7)h_m - (1.56 \log(f_c) - 0.8) \tag{A.4}$$

$$C = 0 \tag{A.5}$$

- metropolitan areas

$$a(h_m) = \begin{cases} 8.29(\log(1.54h_m)^2 - 1.1 \text{ for f } \leq 200 \text{ MHz} \\ 3.2(\log(11.75h_m)^2 - 4.97 \text{ for f } \geq 400 \text{ MHz} \end{cases} \tag{A.6}$$

$$C = 0 \tag{A.7}$$

- suburban environments

$$C = -2[(\log f_c/28)]^2 - 5.4 \tag{A.8}$$

- rural area

$$C = -4.78[\log f_c]\, 2 + 18.33 \log f_c - 40.98 \tag{A.9}$$

The function $a(h_m)$ in suburban and rural areas is the same as for urban (small and medium-sized cities) areas.

Signal to noise ratio

This section describes the computation of the UE signal to noise ratio module.

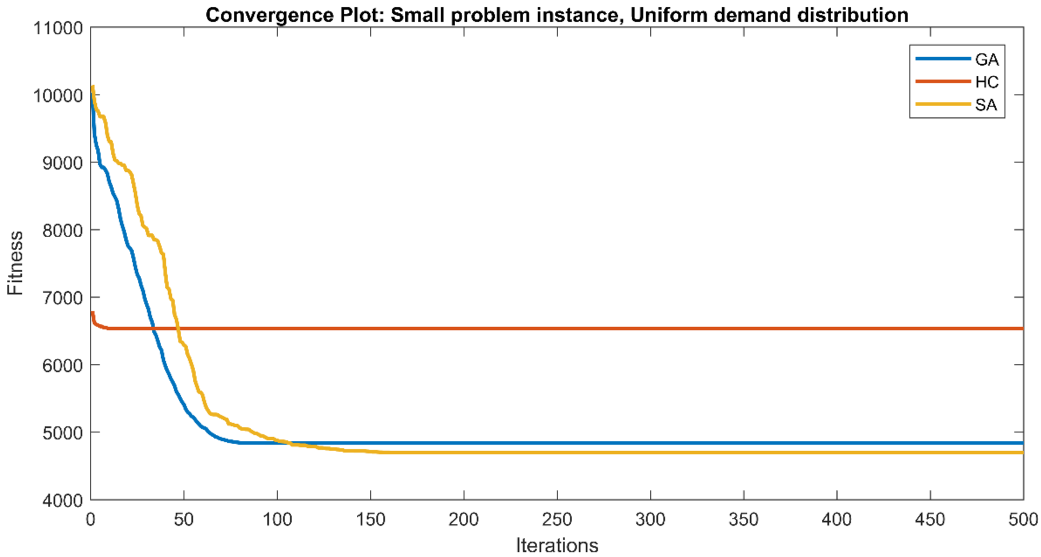
Let *D* be the set of deployed base stations on a service area using the same frequency channel to serve a set *U* of users. The signal to noise ratio of a user (ρ^u) connected to a base station $s \in D$ is given by equation *2.1*.

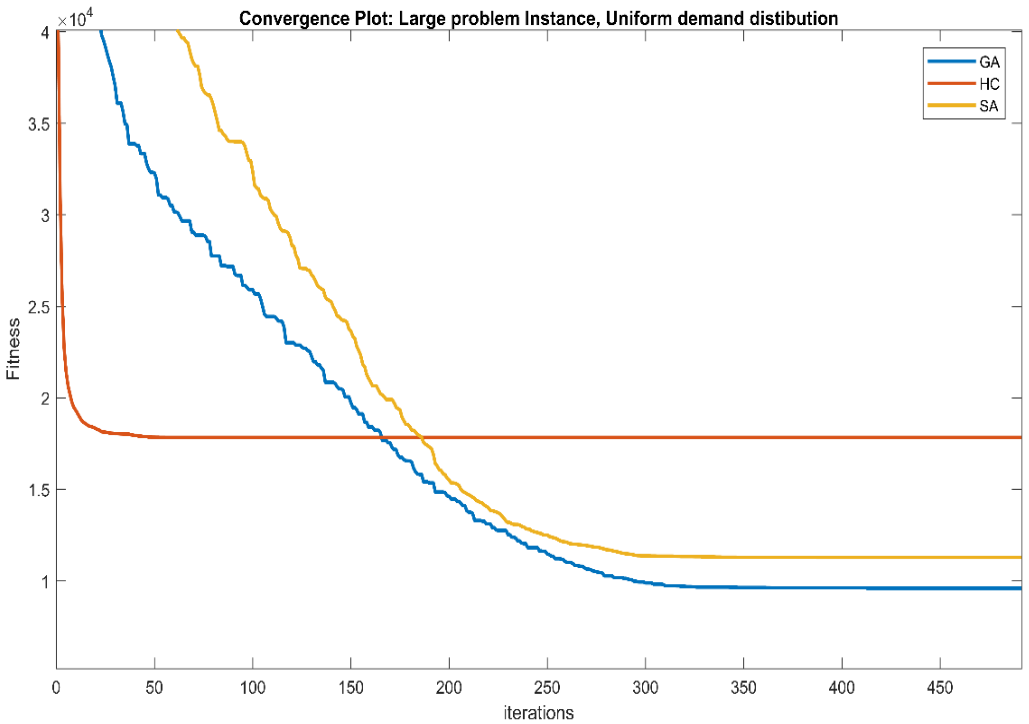
$$\rho^u = \frac{P_{rx(s,u)}}{\sum_{d \neq s}^{|D|} P_{rx(d,u)}} \tag{A.10}$$

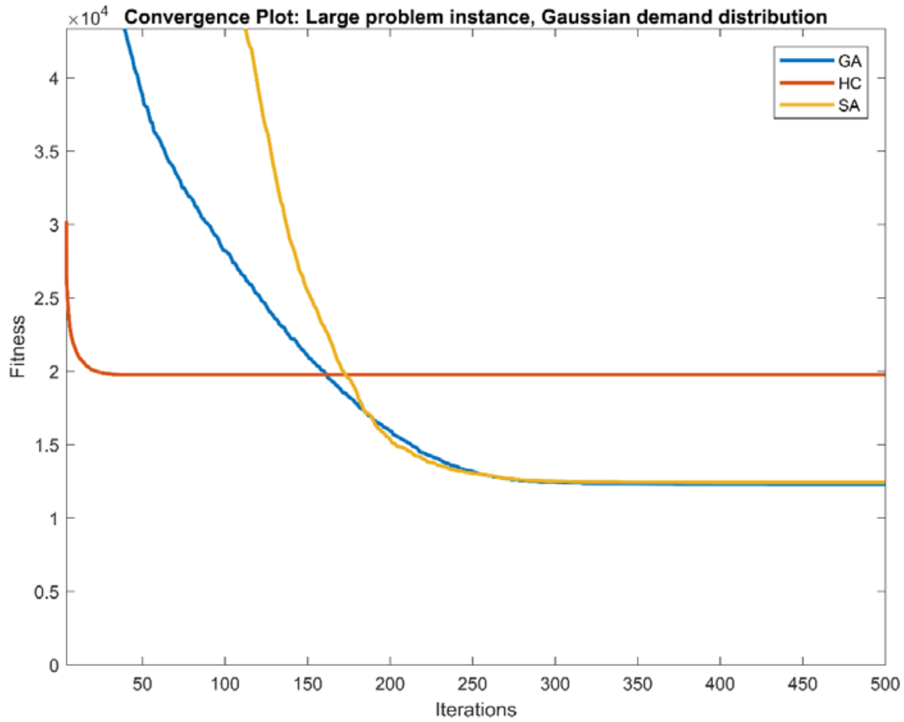
where $P_{rx(d,u)}$ is the received power by base station *u* from base station *d*

B. Appendix

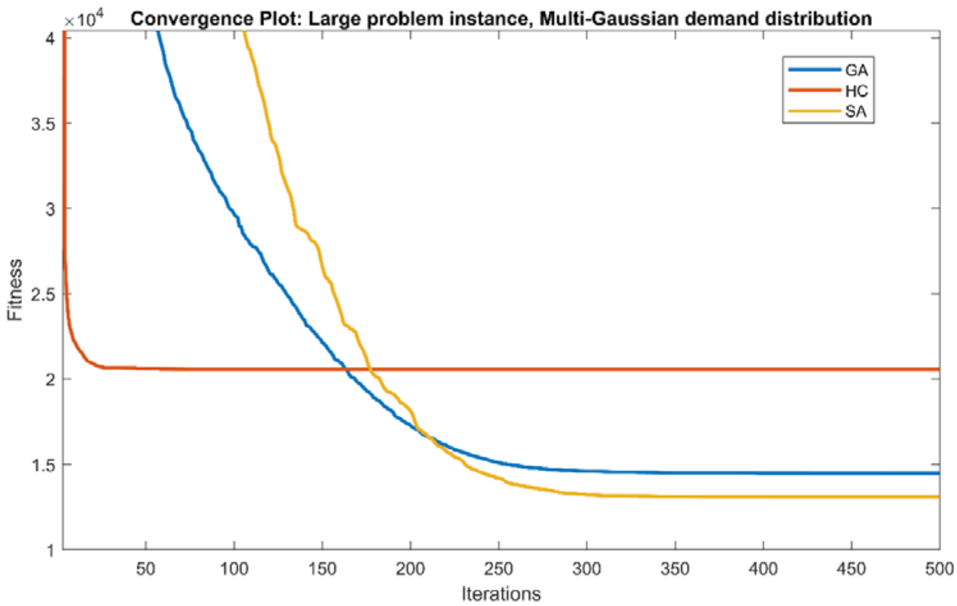
This appendix provides convergence plots to support the results of Chapter 5. The comparable performance between the SA and GA can be observed when the number of iterations is 500,000. However, the fitness of the GA significantly worsened when the number of fitness calls is reduced to 100,000.



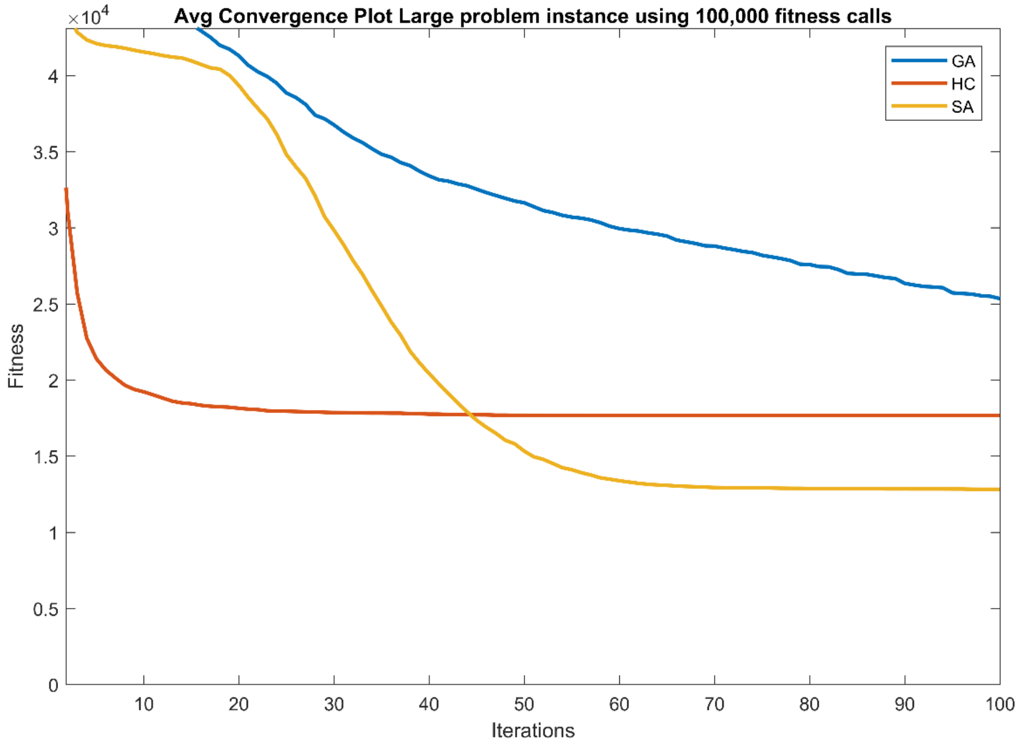




Convergence Plot: Large problem instance, Gaussian demand distribution
×10^4
GA
HC
SA
Fitness
Iterations
0
0.5
1
1.5
2
2.5
3
3.5
4
50
100
150
200
250
300
350
400
450
500



Convergence Plot: Large problem instance, Multi-Gaussian demand distribution
×10^4
GA
HC
SA
Fitness
Iterations
1
1.5
2
2.5
3
3.5
4
50
100
150
200
250
300
350
400
450
500



Avg Convergence Plot Large problem instance using 100,000 fitness calls
×10^4
Fitness
Iterations
GA
HC
SA
0
0.5
1
1.5
2
2.5
3
3.5
4
10
20
30
40
50
60
70
80
90
100

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