Optimisation of Base Station Placement for Indoor Wireless Communications

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Abstract

The development of wireless communication systems has enabled ‘anywhere, anytime’ communication and significantly influenced the working habits of the people in modern society. Engineers responsible for deploying base stations in wireless systems face opposing constraints of maximising the quality and capacity of the system while minimising the interference and cost. In addition, indoor wireless systems must cope with three-dimensional variations in signal strength and limitations in site selection. Consequently, the indoor Base Station Placement (BSP) problem becomes a multi-objective, multi-dimensional optimisation problem. This thesis investigates the BSP problem for indoor wireless communication systems by using mathematical models and optimisation algorithms and considering the effect of several factors on BSP.

Researchers have proposed a number of algorithms to find the optimal solution for the BSP problem. In this thesis, some proposed algorithms are compared to identify the most appropriate algorithm to solve the indoor BSP problem. Based on the advantages and disadvantages of the existing algorithms, a novel hybrid algorithm is developed and its performance is compared to the existing algorithms. It is seen that the proposed hybrid algorithm provides optimal deployments, without significantly compromising accuracy and efficiency.

Although there are several factors that can affect BSP in indoor wireless systems, the effects of three factors, namely call traffic variability, user mobility and call switching technologies on BSP are investigated. Two options are considered for each factor — call traffic can be static or dynamic, users can be fixed or moving and call switching technology can be circuit or packet switched. It is seen that dynamic call traffic, user mobility and circuit switched traffic must be considered in order to identify the optimal BSP. In addition, the BSP problem is extended to multi-floored buildings by considering internal and external potential base station sites. It is seen that the vertically aligned internal base station sites achieve the least call failure rate.

The results obtained from this thesis are intended to provide a practical and useful framework for solving the BSP problem of indoor wireless communication systems.

Dedication

To my grandparents, parents and brother,
who have always encouraged me and given me unfailing love, support and guidance.

Acknowledgments

I would like to express my sincere gratitude to my supervisors, Assoc. Prof. Kevin Sowerby and Dr. Michael Neve. Their invaluable guidance, unfailing patience and inspiring support over the past four years have been instrumental in shaping the quality of this research.

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I would also like to thank my mom, dad and brother for their unconditional love and unfailing support. They have always believed in me and encouraged me to overcome all the problems in life. Finally and most importantly, I would like to thank God for everything.

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Glossary

Abbreviations and Acronyms

BFS	Brute Force Search
CAC	Call Admission Control
CBR	Constant-Bit-Rate
CDMA	Code Division Multiple Access
CIR	Carrier-to-Interference Ratio
D/F/C	Dynamic traffic/ Fixed users/ Circuit switched calls
D/M/C	Dynamic traffic/ Moving users/ Circuit switched calls
D/M/P	Dynamic traffic/ Moving users/ Packet switched calls
FDMA	Frequency Division Multiple Access
GEN	Genetic Algorithm
GoS	Grade of Service
GRE	Greedy Algorithm
LTE	Long Term Evolution
NGA	Ngadiman's Algorithm
OFDMA	Orthogonal Frequency Division Multiple Access
RCR	Reduction Estimation - Combinatorial Optimisation - Reduction Approximation
S/F/C	Static traffic/ Fixed users/ Circuit switched calls
SIR	Signal-to-Interference Ratio

TDMA	Time Division Multiple Access
VBR	Variable-Bit-Rate
WiMAX	Worldwide Interoperability for Microwave Access

Symbols

G_p	Processing gain
N_{bs}	Number of potential base station sites
N_u	Number of potential user locations
N_{u_o}	Number of office bearers
N_{u_v}	Number of visitors
P_{max}	Maximum signal power transmitted by a user
P_{min}	Minimum required signal power received by a user
P_{ru}	Received signal power of user u
P_{tu}	Transmitted signal power of user u
Q_f	Forward link SIR threshold
Q_r	Reverse link SIR threshold

Chapter 1

Introduction

The development of wireless communications is one of the major engineering success stories of the last 25 years in terms of scientific progress as well as impact on society [1, p3]. Wireless communication systems have enabled 'anywhere, anytime' communication and influenced lives of people in the modern world [1, p3] [2, p1]. The first generation (1G) of (cellular) wireless communication systems, introduced in the 1980s, were based on analog technology and paved the way for the wireless revolution [1, p5]. Digital technology was introduced in the second generation (2G) wireless systems (in the 1990s) which provided better spectral efficiency and voice quality [2, p1]. Third generation (3G) wireless systems, developed in the early 2000s, spurred spectacular growth in the popularity of wireless communication services [2, p1]. The 3G systems led to the proliferation of wireless mobile devices that allow internet browsing and multimedia reception as well as conventional voice calls [1, p8]. Although 3G systems are still being deployed, the possible candidates of fourth generation (4G) systems, such as the Long Term Evolution (LTE) and Worldwide Interoperability for Microwave Access (WiMAX) are already being deployed in many countries [2, p1].

Along with the development and widespread use of outdoor wireless systems, the demand for indoor wireless systems has been increasing rapidly [3, p1] [4, pp71-72]. Indoor systems have significant concentrations of potential users, such as within high-rise office buildings, shopping malls and airports [5, p1] [6, p2]. In many countries, 60-80% of calls and 90% of data traffic occur indoors, making it important to provide good indoor coverage along with the outdoor coverage [3, p1] [4, p 72]. The coverage for outdoor systems is provided by several high power base stations known as macrocells or microcells[1] [3, pp15-17] [6, p2]. In contrast, low power base stations, known as picocells or femtocells[2], have been proposed as cost effective

[1]A macrocell has a coverage range of 1-10km and is installed in rural areas whereas a microcell has a coverage range of less than 1km and is installed in urban areas [3, pp15-17] [6, p2].

[2]A picocell has a coverage range of 30-200m whereas a femtocell has a coverage range of less than 30m [3, p35] [6, p2].

solutions to provide indoor coverage [2, p1] [3, p36]. Regardless of the developments in wireless technologies and systems, optimal system deployment remains an important requirement for achieving high performance [2, p1].

Engineers responsible for deploying wireless systems are concerned with maximising the quality and capacity of the system while minimising the interference and cost [5, p3]. In practice, capacity, quality, interference and cost are significantly interdependent. For example, a system with a small number of base stations will provide low capacity but will suffer low levels of co-channel interference (i.e. quality is high) and will be low cost. Conversely, a system with a large number of base stations will provide high capacity but will suffer high levels of co-channel interference (i.e. quality is low) and will be high cost. Fundamentally, for a fixed cost, a compromise between capacity and quality is required, and co-channel interference is the limiting factor. Levels of co-channel interference are heavily dependent on the physical base station deployment and so careful base station placement is of critical importance.

Some algorithms have been proposed for the placement of base stations in outdoor wireless communication systems [7–9]. However, the increasing popularity of indoor systems requires the identification of strategies for effectively deploying base stations in indoor environments [4, p72] [10] [11, p316] . In outdoor systems, the BSP problem is usually two-dimensional as the base stations and mobile users are horizontally displaced from each other [12, p34]. In contrast, the BSP problem in indoor systems is more complicated as the coverage must be provided in three-dimensional environments [5, p6]. The engineers deploying indoor systems must account for the (three-dimensional) variations in signal strength and limitations in site selection along with the issues of capacity, quality, interference and cost [5, p6]. Consequently, the indoor Base Station Placement (BSP) problem becomes a multi-objective, multi-dimensional optimisation problem with many opposing constraints.

The aim of this thesis is to solve the BSP problem for indoor wireless communication systems using mathematical models and optimisation algorithms and considering the effect of several factors on BSP. The main objectives of this thesis are:

- Identify/develop an appropriate algorithm (possibly from existing algorithms) to solve the BSP problem for indoor wireless communication systems;
- Identify a system model for BSP in indoor wireless communication systems considering the effect of
  - call traffic variability,
  - user mobility and
  - call switching technologies; and

- Identify the optimal BSP for multi-floored buildings (by considering internal and external base station sites).

As shown in Fig. 1.1, this thesis comprises of twelve chapters and the three objectives are the subjects of Chapters 5-7, Chapters 8-10 and Chapter 11, respectively. The publications relating to this research are in [13–15]. An overview of the chapters (and the contributions[3]) in this thesis is as follows.

Chapter 2 (Wireless Communication Systems — An Overview) discusses the fundamentals of wireless communication systems including the concepts of cellular systems and frequency sharing; the effects of the propagation environment on the transmitted signals; the concept of interference and the importance of power management in wireless systems.

Chapter 3 (CDMA System Deployment) discusses the fundamentals of CDMA and reviews the deployment strategies developed in the literature for Base Station Placement (BSP). In addition, *the contributions of this thesis are discussed in the context of the existing literature.*

Chapter 4 (Optimisation and Wireless System Modelling) discusses the concept of optimisation and the stages of solving a problem using optimisation. The concept and stages of optimisation are also applied to the indoor Base Station Placement (BSP) problem for CDMA systems. The outcome of this chapter is the development of mathematical models for BSP optimisation which are used throughout this thesis.

Chapter 5 (Existing Algorithms for Base Station Placement — A Comparison) implements four existing algorithms, namely the Brute Force Search (*BFS*), Genetic Algorithm (*GEN*), Greedy Algorithm (*GRE*) and Ngadiman's Algorithm (*NGA*) to solve the indoor BSP problem. The performances[4] of the four algorithms are compared using a case study (Case Study 1) to identify the advantages and disadvantages of each algorithm.

Chapter 6 (Development of a Hybrid Algorithm – *RCR*) develops a novel hybrid algorithm, *Reduction Estimation - Combinatorial Optimisation - Reduction Approximation (RCR)* for BSP optimisation, by combining the advantages of the existing algorithms. The performance of *RCR* is also compared to the four existing algorithms (*BFS*, *GEN*, *GRE* and *NGA*) using Case Study 1, to identify the most appropriate algorithm for BSP optimisation.

[3]The original contributions of this thesis are highlighted in blue.

[4]The performance of each algorithm is judged by its accuracy (i.e. the correctness of solution) and efficiency (i.e. the speed of execution).

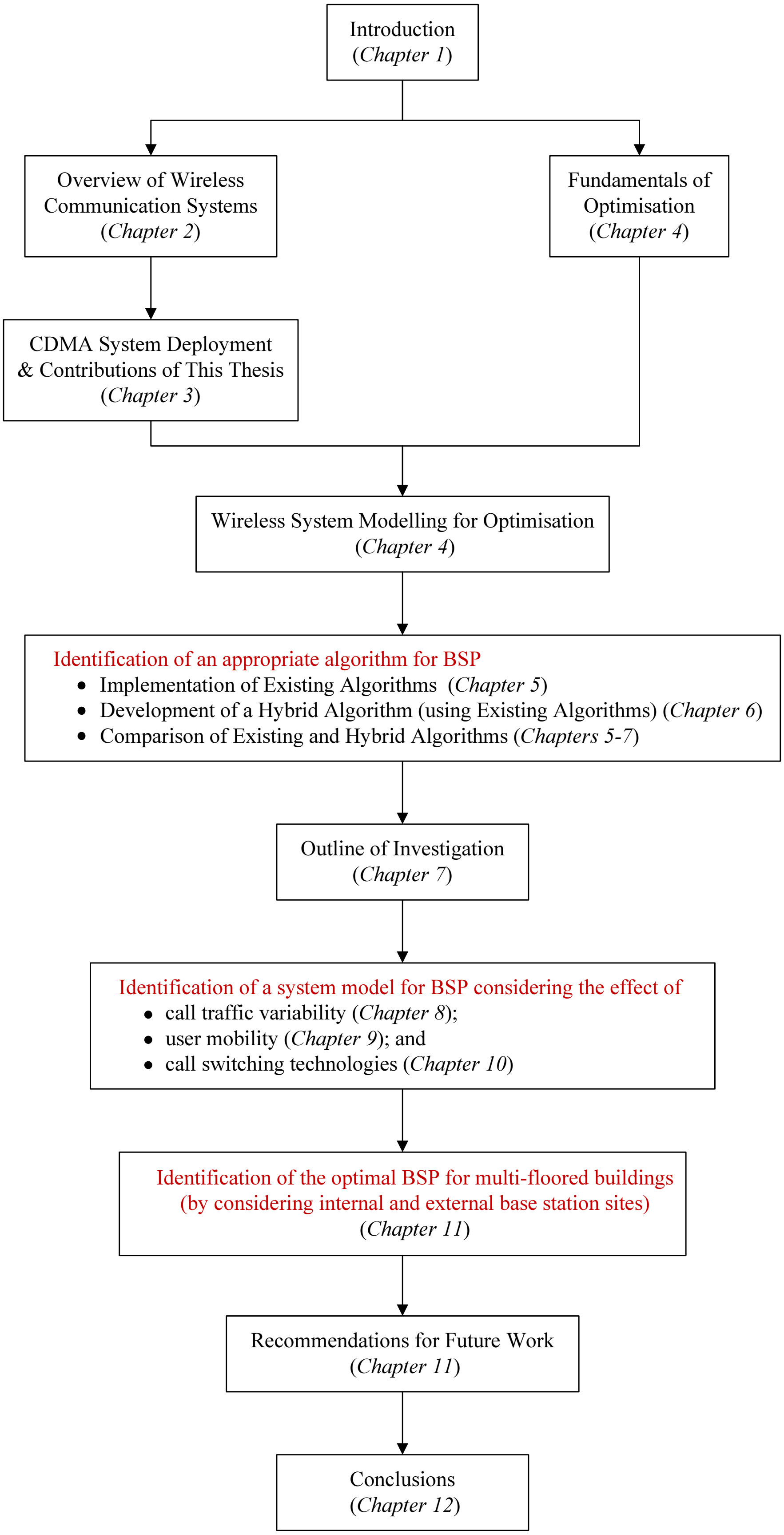


Figure 1.1: Structure of this thesis. The objectives are highlighted in red.

Chapter 7 (Comparison of Algorithms and Outline of Investigation) further compares the five algorithms (*BFS, GEN, GRE, NGA* and *RCR*) in a variety of environments, using two more case studies (Case Studies 2 and 3) which are based on the path loss values found by in-building experimental measurements. In addition, the investigations in Chapters 8-11 are outlined and four system models (i.e. System Models A-D) are defined in this chapter.

Chapter 8 (Effect of Call Traffic Variability on Base Station Placement) investigates the effect of call traffic variability (i.e. variations in call arrivals and departures) on the BSP problem. The two options considered for call traffic are 'static' and 'dynamic'. The implementations of System Models A and B are discussed to understand how static and dynamic call traffic are modelled for indoor users. The optimisation results of System Models A and B are compared to investigate the effect on BSP optimisation. Comparison of the BSP results for static and dynamic traffic is an advance on previous studies, which generally address the two options separately.

Chapter 9 (Effect of User Mobility on Base Station Placement) investigates the effect of user mobility (i.e. the movement of users) on the BSP problem. The two options considered for user mobility are 'fixed' and 'moving'. The implementation of System Models B and C are discussed to understand how mobility of indoor users is modelled. The optimisation results of System Models B and C are compared to investigate the effect on BSP optimisation. This is the first time that models to include the mobility of indoor users are considered for BSP optimisation.

Chapter 10 (Effect of Call Switching Technologies on Base Station Placement) investigates the effect of call switching technologies on the BSP problem. The two options considered for call switching are 'circuit switched' and 'packet switched'. The implementation of System Models C and D are discussed to understand how circuit and packet switching technologies are modelled for indoor users. The optimisation results of System Models C and D are compared to investigate the effect on BSP optimisation. Packet switched traffic (with different distributions[5]) considered in this chapter is a novel contribution to the field of BSP optimisation.

Chapter 11 (Optimisation of Multi-Floored Buildings and Future Work) investigates a unique BSP problem for multi-floored buildings with 'internal' and 'external' potential base station sites, dynamic traffic, moving users and circuit switched calls. A real office building is

[5]Constant-Bit-Rate (CBR) and Variable-Bit-Rate (VBR) packet traffic are considered in this thesis. CBR traffic is modelled by generating a constant number of packets per frame whereas VBR traffic is modelled by generating variable number of packets per frame (using three distributions, namely Poisson, Negative Binomial and Pareto).

analysed and the optimisation is performed first by considering only 'internal' base station sites and then, by considering both 'internal' and 'external' sites. In addition, the potential areas for future work are identified in this chapter.

Chapter 12 (Conclusions) presents the main findings and discusses the key conclusions of this thesis. These conclusions are likely to be useful for the deployment of indoor wireless systems.

Appendix A describes how the in-building experimental measurement campaigns were performed in [5] to measure the path loss values used in this thesis.

Appendix B presents additional results for the investigations performed in Chapters 8-10 of this thesis.

Chapter 2

Wireless Communication Systems — An Overview

2.1 Introduction

Wireless communication is the transfer of information (as signals) over a distance using the electromagnetic frequency spectrum without use of wires [16, p9]. One of the simplest wireless communication systems is the broadcasting system, which transmits the same information to all the users, as shown in Fig. 2.1 [1, pp8-9]. The system has one-way traffic i.e. the broadcasting station can only transmit information to the users but the users cannot transmit any information back to the station. Since there is one-way communication and the same information is sent to all the users, an unlimited number of users can receive information from a station. The planning of a broadcasting system focuses on the selection of the site and equipment to maximise the coverage and does not require any knowledge about the number of users [5, p4].

In comparison to broadcasting systems, the planning of cellular systems is more complicated [5, p4]. The cellular systems can have two-way communication with different information being transmitted to (and from) different mobile users, as shown in Fig. 2.2 [1, pp10-11]. Thus, both the base stations and the mobile users are transceivers (i.e. transmitters and receivers). In Fig. 2.3, a two-way connection between a base station and a mobile is shown. The transmission of the signal from the base station to the mobile is called *forward link* or *downlink* transmission whereas the transmission of the signal from the mobile to the base station is called *reverse link* or *uplink* transmission.

Since the base stations and the users can both transmit and receive signals, a limited number of users can connect to a base station in a cellular system. In order to provide connectivity to a large number of users (i.e. have high capacity), the frequency spectrum must be shared and utilized effectively in cellular systems. The concept of cellular systems and frequency sharing

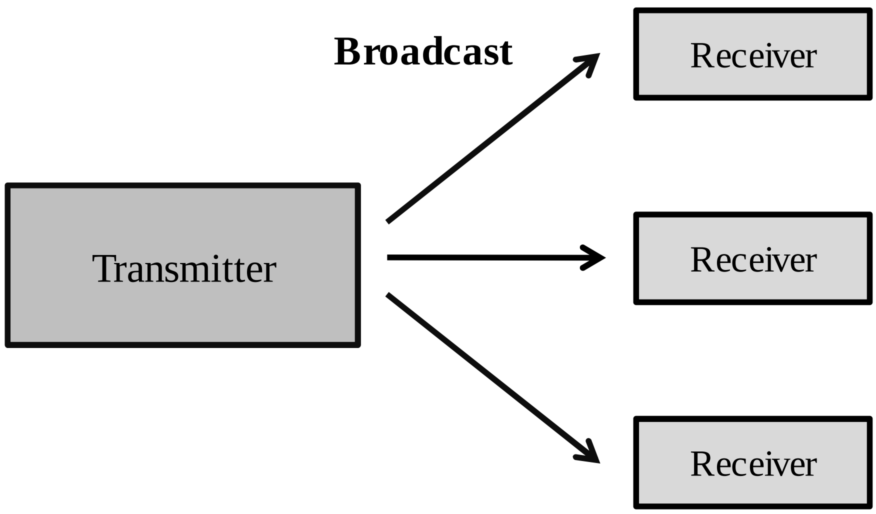


Figure 2.1: Principle of broadcasting systems. A transmitter sends the same information to all the receivers.

is described in Section 2.2. In Section 2.3, the effects of the propagation environment on the transmitted signals are discussed and modelled. In Section 2.4, the concept of interference and the importance of power management in cellular systems is discussed. The chapter is summarised in Section 2.5.

2.2 The Cellular Concept

In cellular systems, the frequency spectrum available is limited and has to be shared by different users so that a large number of users can connect simultaneously [1, p11] [5, p4]. This is achieved by dividing the total geographical area into subareas called *cells* and allocating a subset of the available channels to each cell. The cells are frequently stylised as hexagons[1] as shown in Fig. 2.4.

Each cell has a fixed base station and several mobile users. The mobile users within a cell share[2] the frequency channels allocated to the cell. The neighbouring cells are allocated different channels to avoid interference [18, p346]. However, as the spectrum is limited, the cells which are (sufficiently) spatially separated are allocated the same frequency channels and this is referred to as *frequency reuse*. In Fig. 2.4, the frequency spectrum is shared by a cluster of seven cells and the cells with the same numbers use the same frequency channels. The frequency

[1]The actual cell is amorphous and the size depends on several factors including the number of users and the topography of the land [17, p58]. However, the hexagon shape is chosen for conceptual discussion.

[2]Multiple access schemes (like FDMA, TDMA, CDMA and OFDMA), discussed in Chapter 3, determine how the (multiple) users share the resources in a cell [1, p365].

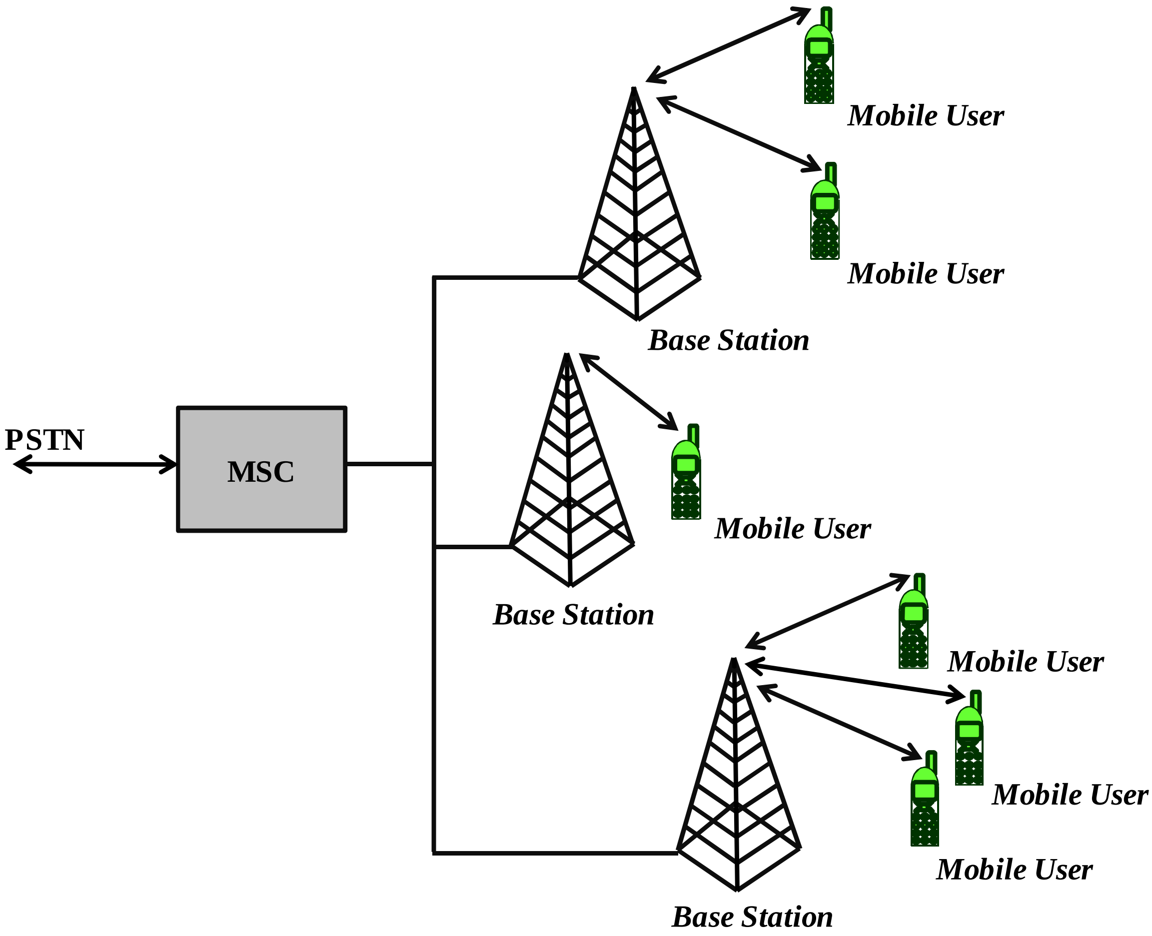


Figure 2.2: Principle of cellular systems. The mobile users and base stations send and receive different information. The base stations are connected to the Mobile Switching Centre (MSC) which is in turn connected to the Public Switch Telephone Network (PSTN).

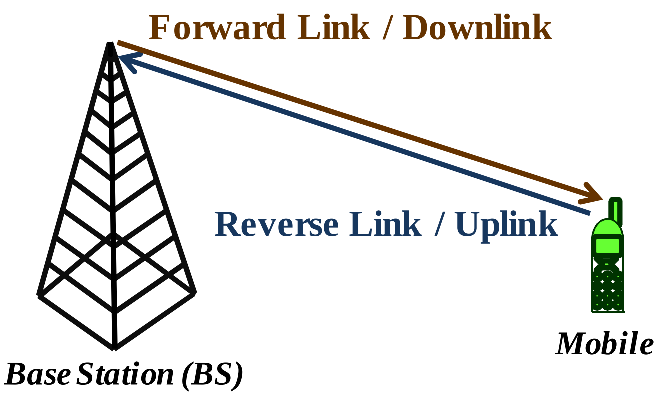


Figure 2.3: Concept of forward and reverse link transmissions in cellular systems.

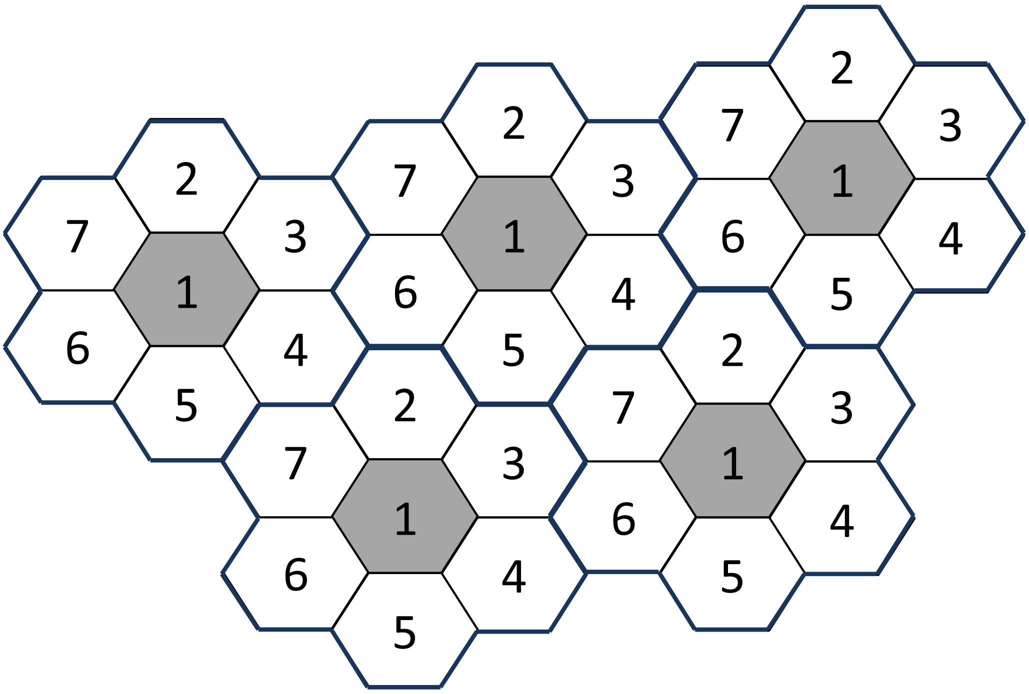


Figure 2.4: Example of the cellular frequency reuse concept. Cells with the same numbers are co-channel cells i.e. they use the same frequency channels. A cluster of cells is outlined in bold (blue) and replicated over the total area. In this example, there are seven cells in a cluster and hence each cell uses one-seventh of the total frequency channels (i.e. the frequency reuse factor is $\frac{1}{7}$).

is reused only if there is enough distance between the cells in order to minimise *co-channel interference* i.e. the interference between two cells using the same frequency channels [1, p11].

The frequency spectrum, available to cellular systems, can be either *licensed* or *unlicensed* [19, pp8-12]. Licensed spectrum is leased by a network operator (for exclusive use), whereas unlicensed spectrum is freely available to the general public (although usually with some constraints) [1, pp34-35]. In the licensed spectrum, there are virtually no constraints on the transmitted power and the interference is only from the system itself [20, pp120-121]. Thus, the deployment of the system is critical to minimise interference. However, in the unlicensed spectrum, there is a regulatory limit on the maximum transmission power and there can also be interferences from other devices operating on the same spectrum. Hence, the design of the two types of systems (i.e. licensed and unlicensed) is very different and this thesis is based on licensed cellular systems.

2.3 Radio Propagation in Cellular Systems

In a cellular system, the signal transmitted by the base station or mobile user is affected by the radio propagation environment. In this section, the phenomena affecting signal propagation and the characteristics of (and the variations in) the received signal are discussed. Then, the concept of path loss and the models to predict path loss are described. Finally, it is discussed how the path loss is estimated (for solving the base station placement problem) in this thesis.

As shown in Fig. 2.5, the transmitted signal can have several components obtained by propagation using *directly transmitted*, *diffracted*, *reflected* and *scattered* paths [2, p8] [12, p11].

- **Directly transmitted path** is the shortest propagation path between the transmitter and the receiver [2, p8].
- **Diffracted path** is the path followed by the signal when it “bends” around edges of obstacles (like partitions and walls) [2, p8].
- **Reflected path** is the path followed by the signal reflected by objects (like walls and ceilings) which are larger than the wavelength of the signal [2, p8].
- **Scattered path** is the path of the signal scattered (in several directions) after hitting objects (like pots and knobs) which are smaller than the wavelength of the signal [2, p8].

Thus, as shown in Fig. 2.5, the transmitted signal encounters many obstacles and propagates using multiple paths. This phenomenon is known as *multipath propagation* [12, p11].

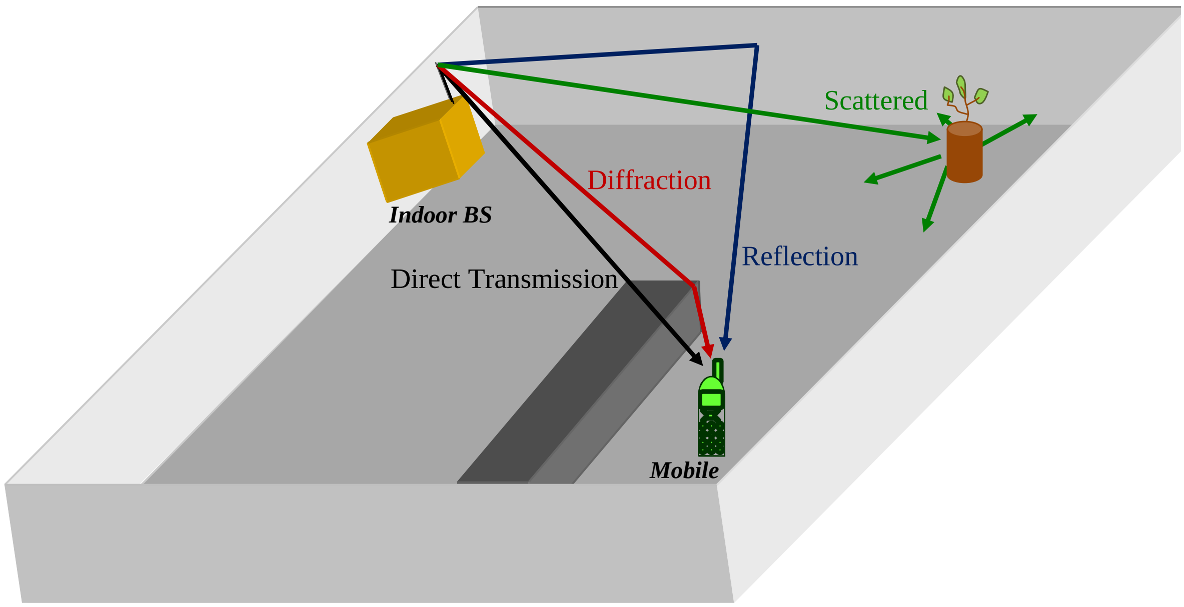


Figure 2.5: The propagation paths between an indoor base station and a mobile — directly transmitted, diffracted, reflected and scattered paths.

The received signal is the summation of the components of the transmitted signal. The components can have different amplitudes and phases which add constructively or destructively resulting in *fading* [2, p10]. Generally, the received signal has short-, medium- and long-term variations [2, p12] [12, p12].

Short-term variation, also known as *fast fading*, is the rapid fluctuation in the instantaneous received signal caused by the constructive or destructive addition of the multipath components. The distance between successive fades is in the order of half a wavelength [6, p9] [21, p23]. The fluctuation can be typically modelled using either a Rayleigh or a Rician distribution [2, p12].

Medium-term variation, also known as *shadowing*, is the variation in signal due to obstacles that shadow the receiver. It is observed over distances in the order of tens of wavelengths and can be typically modelled using log-normal distribution [2, p12] [21, p24].

Long-term variation is the variation observed in the signal when the distance between the transmitter and receiver changes. The variation can often be characterised by an inverse power law relationship, $\frac{1}{d^n}$, where d is the distance between the transmitter and the receiver and n is the path loss exponent[3] [2, p13].

In [22, pp8-9], an indoor propagation experiment was conducted to obtain the characteristics of a typical received signal. A fixed 1.8 GHz transmitter was deployed and the received signal was measured using a mobile test receiver (moving over a defined path). The set up of the experiment is shown in Fig. 2.6. Fig. 2.7 shows the received signal (in blue) measured along the path and the *local area mean*[4] of the received signal (in red) over a 1m radius. The local area mean is the mean received signal averaged over a sufficient distance so that the short-term variations (due to fading) are eliminated, but medium-term variations (due to shadowing) and long-term variations (due to distance-dependence) are represented.

If P_r is the power of the local mean received signal (in dBm) and P_t is the power of the transmitted signal (in dBm) , the *mean path loss* (i.e. the reduction in the mean signal power) between a transmitter and receiver, PL (in dB) is given by

$$PL = P_t - P_r.$$

Several propagation models have been proposed to estimate PL [2, pp13-24]. The proposed models are broadly of two types — *empirical* and *deterministic* [6, pp17-25].

- **Empirical models** are developed from experimental measurements of the received signal power [6, p17]. The path loss is typically modelled as an exponentially varying term depending on the distance between the transmitter and the receiver and additional terms to account for penetration losses [3, p111] [6, p18]. Even though empirical models are simple to implement, their applicability cannot be generalised as they lack a physical basis for the observed phenomena [6, p20].

- **Deterministic models** are developed by modelling the physical properties and geometry of the environment. The path loss values are found using electromagnetic analyses which take the features of the environment into account [3, p112]. Deterministic models can be accurate but their disadvantages include high complexity, lengthy computation times and restricted problem sizes (due to limited computing resources), making them unsuitable for everyday applications (at the present time) [6, pp20-21].

In this thesis, the accurate prediction of path loss and the received signal is of paramount importance. Due to the limitations in the empirical and deterministic models [3, pp113] [23, p6], this thesis is based on measured[5] propagation data collected in the actual environments [5] [24].

[3] The value of the path loss exponent depends on the propagation environment [2, p13].

[4] Local area mean is also referred to as *sector area mean* [6, p9].

[5] Appendix A describes how the measurement campaigns were performed in [5].

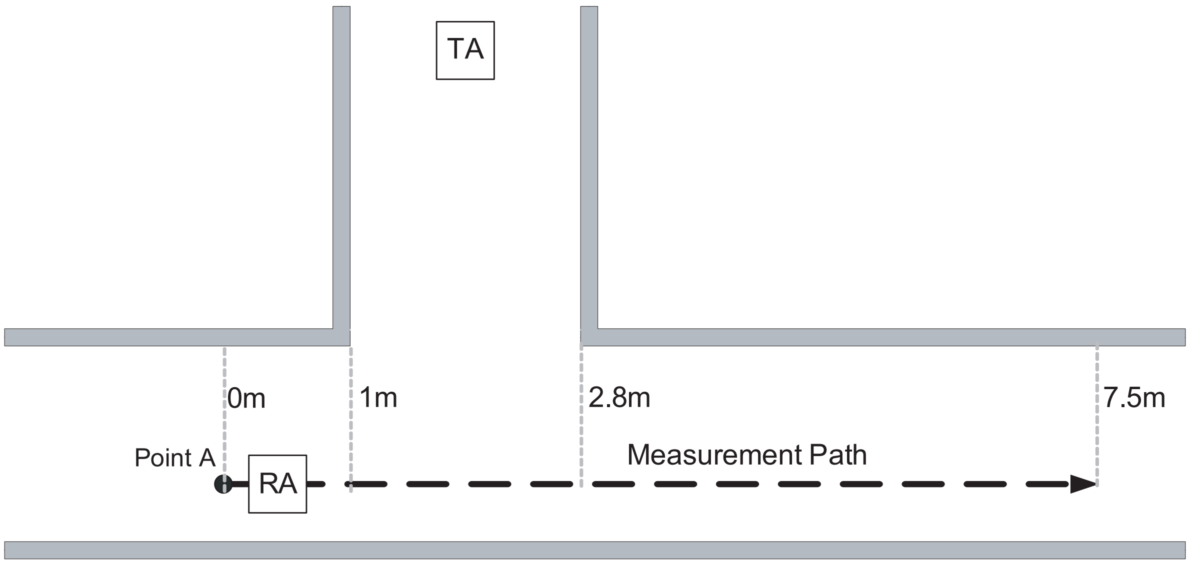


Figure 2.6: Set up of a simple propagation experiment to obtain the characteristics of the received signal. TA is a fixed 1.8 GHz transmitter and RA is a moving receiver. Measurements are taken while the RA moves along the trajectory shown by – – –. (*Courtesy of Derek Lee [22].*)

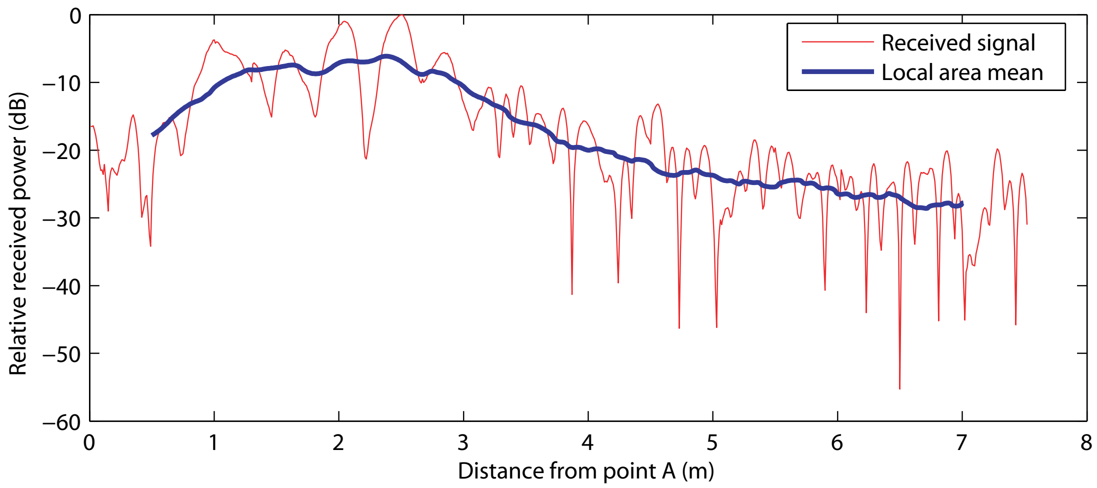


Figure 2.7: Received signal strength along the measurement path for the experiment shown in Fig. 2.6. (*Courtesy of Derek Lee [22].*)

The advantage of this approach is that no assumptions are made on how signals propagate and thus, the analyses can be conducted with great confidence [12, p24]. Although the conclusions drawn from the analyses are strictly applicable to the buildings and geometries considered, they provide an insight to other buildings of similar construction.

2.4 Interference in Cellular Systems

Interference[6] and *noise*[7] can detrimentally impact the signal at the receiver [1, pp37-44]. In this section, the concept and effects of interference and the importance of (transmission) power management in cellular systems are discussed.

Each base station and user receives a *desired* signal and generally, some *undesired* signals. The desired signal is the transmitted signal (after path loss) and the undesired signals are the interferences. Examples of desired signals and interferences in the forward and reverse links are shown in Figs. 2.8 and 2.9, respectively.

The ratio of the desired signal power to the sum of the interference powers is known as *Signal-to-Interference Ratio (SIR)* [1, p37], i.e.

$$\mathrm{SIR} = \frac{\text{Desired signal power}}{\sum \text{Interference power}}.$$

A mobile user connects to a base station only if the SIR is above a defined threshold, known as the *SIR threshold,* in both the forward and reverse links.

Generally, as a (connected) mobile user moves away from a base station and closer to interferers, the SIR decreases and can go below the defined threshold. Thus, in cellular systems, the base stations must be able to *handover*[8] the mobile user to another base station so that the user can maintain connectivity while moving [4, p9] [17, p10]. Fig. 2.10 shows the *inter-cell handover*[9] process[10] as a mobile user moves from one cell to another.

To increase the SIR in a link, one solution might be to increase the transmitted power (of the desired signal). However, the increase in transmitted power will increase the interference for other links and decrease their SIRs. Thus, the effect on the entire system must be considered before changing the transmitted power of a signal. If the transmission powers of all the

[6] Interference can be the signal to (or from) another mobile user in the same cell, an adjacent cell or a co-channel cell [17, p67].

[7] The noise can be thermal noise and/or noise due to man-made emissions and amplifiers (and mixers) at receiver [1, pp38-39].

[8] Handover is also referred to as *handoff.*

[9] Inter-cell handover is the process of transferring a mobile user from one base station to another. Handover can also be *intra-cell*, in which the mobile user is transferred from one frequency channel to another on the same base station (to mitigate a fade).

[10] The details of the handover process are discussed in Chapter 3.

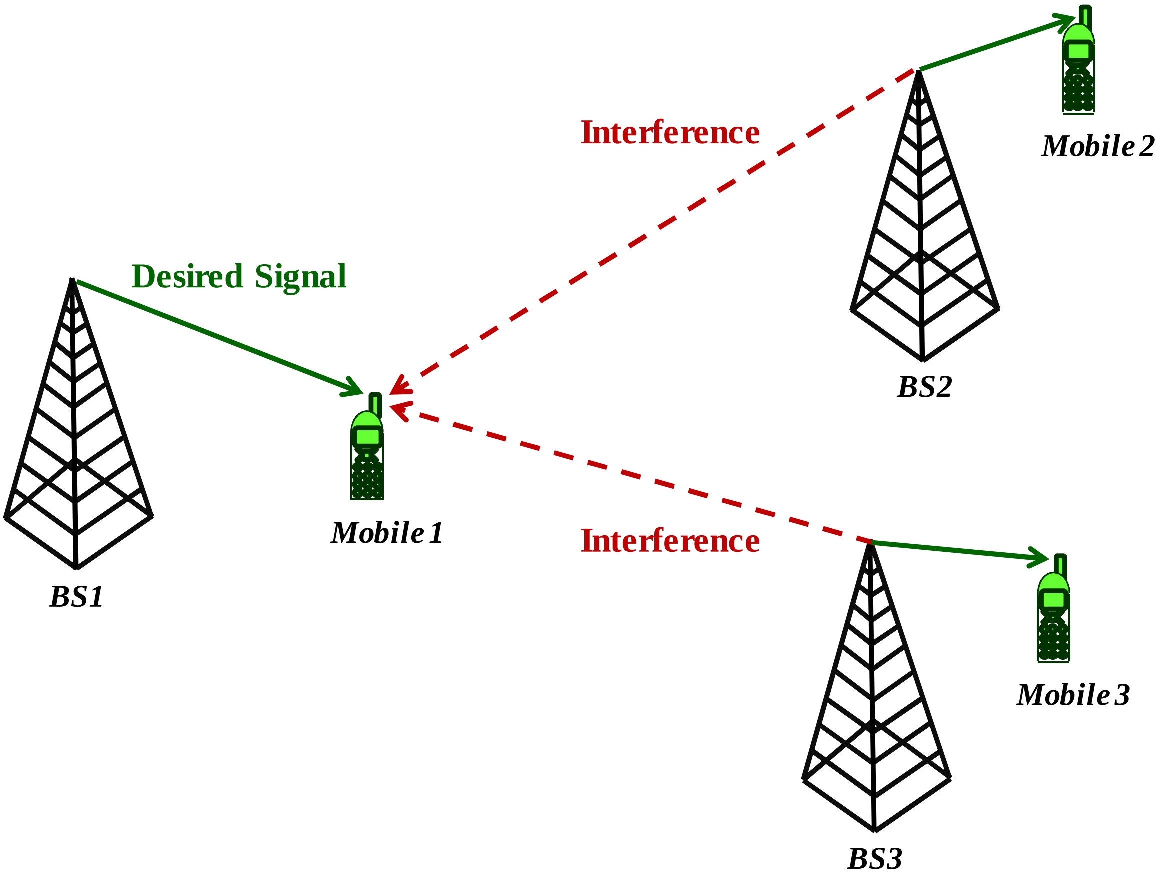


Figure 2.8: The desired signal and interferences in the forward link (for Mobile 1). The ratio of the desired signal power and the total interference signal powers is the forward link Signal-to-Interference Ratio (for Mobile 1).

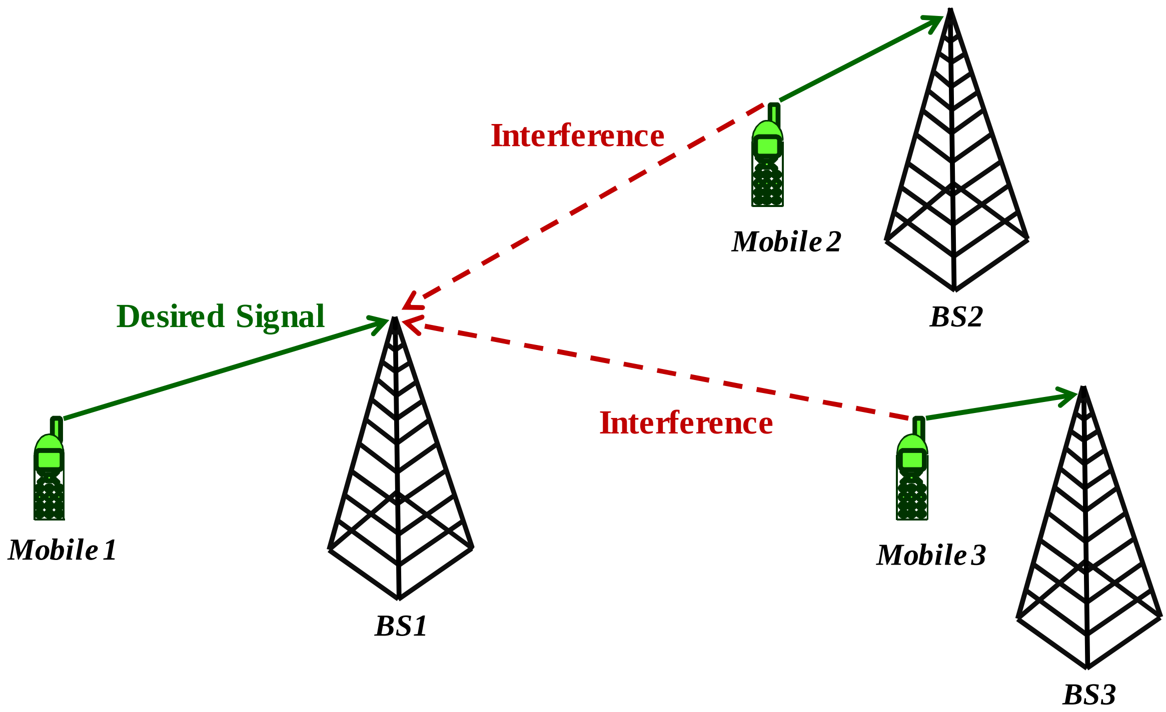


Figure 2.9: The desired signal and interferences in the reverse link (for Base Station 1 (BS1)). The ratio of the desired signal power and the total interference signal powers is the reverse link Signal-to-Interference Ratio (for BS1).

base stations and mobile users are increased (or decreased) proportionately, the SIR will not be affected. However, very high powers can lead to inefficient use of energy, resulting in low battery life. On the other hand, very low powers can lead to dominance of noise, resulting in no connectivity. Thus, the transmission power needs to be managed to minimise the effect of interference and noise. The power management is performed using *power control* schemes[11].

The frequency reuse (and interference) depends on the multiple access scheme[12] whereas the radio propagation is influenced by the environment. Thus, the system planners deploy cellular systems based on the multiple access scheme and the propagation environment [5, p3]. This thesis investigates the Base Station Placement (BSP) problem considering CDMA (for multiple access) and indoor environments (for propagation). In Chapter 3, the details of CDMA (and other multiple access schemes) are discussed with a literature review on the deployment strategies developed for BSP.

[11]The typical power control schemes are discussed in Chapter 3.

[12]Multiple access schemes (like FDMA, TDMA, CDMA and OFDMA) determine how the (multiple) users share the resources in a cell [1, p365].

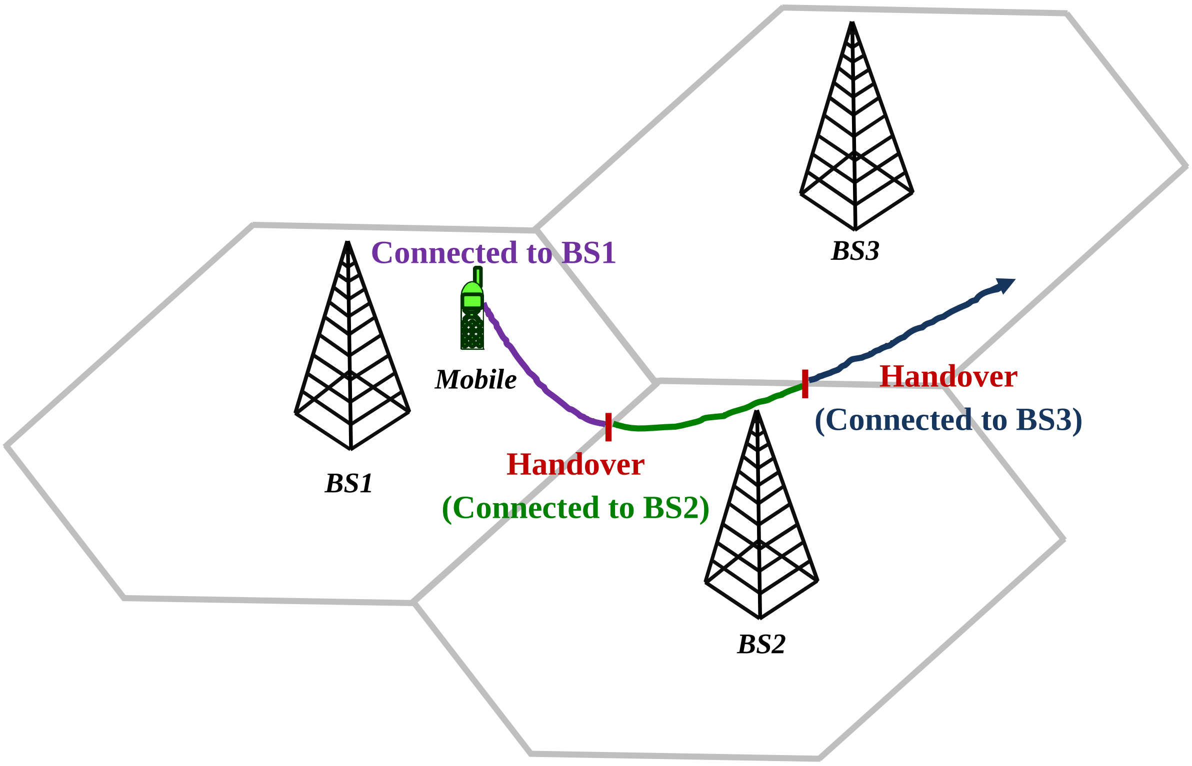


Figure 2.10: Concept of inter-cell handover. The mobile user is initially connected to Base Station 1 (BS1) and starts moving on the shown path. As the user enters the cell of Base Station 2 (BS2), it connects to BS2 if the SIR from BS1 goes below the threshold and the SIR from BS2 is above the threshold. Similarly, BS2 handovers the user to BS3 when the user enters the third cell.

2.5 Summary

In this chapter, the fundamentals of wireless communication systems have been discussed. In cellular systems, there is two way communication between the mobile users and the base stations. As the frequency spectrum is limited, the frequency channels are shared among the cells. The frequency is reused in cells which are (sufficiently) spatially separated to minimise co-channel interference. The frequency spectrum can be either licensed (leased by the network operator) or unlicensed (freely available to the public). This thesis considers licensed cellular systems.

The signal transmitted from a base station or a user encounters many obstacles and propagates using multiple paths. The received signal is the summation of the components of the transmitted signal obtained by multipath propagation and can have short-, medium- and long-term variations. The propagation models proposed to predict the path loss of the transmitted signal can be broadly classified as either empirical or deterministic. This thesis is based on measured propagation data collected in the actual environments so that the analyses can be performed with confidence. Although the conclusions drawn from the analyses are strictly applicable to the buildings and geometries considered, they provide an insight to other buildings of similar construction.

The received signal is affected by interference and noise. The ratio of the desired signal power to the sum of the interference powers is known as Signal-to-Interference Ratio (SIR) and it must be above the SIR threshold in both the forward and reverse links for successful communication. As the user moves away from a desired base station and the SIR goes below the threshold, the base station tries to handover the user to another base station. High transmission powers can lead to inefficient use of energy whereas low powers can lead to dominance of noise. Thus, the transmission powers of the base stations and the users are managed (to minimise the effect of interference and noise) using power control schemes.

The design of cellular systems is based on the multiple access scheme and the propagation environment. The focus of this thesis is the placement of base stations considering CDMA (for multiple access) and indoor environments (for propagation). In Chapter 3, the details of CDMA (and other multiple access schemes) are discussed with a literature review on the deployment strategies developed for BSP.

Chapter 3

CDMA System Deployment

3.1 Introduction

In Chapter 2, the fundamentals of wireless communication systems were discussed. In a cellular wireless communication system, each cell has a fixed base station which connects to multiple mobile users simultaneously. The users share the available resources in the cell using multiple access schemes like Frequency Division Multiple Access (FDMA), Time Division Multiple Access (TDMA) and Code Division Multiple Access (CDMA).

The multiple access in a (cellular) wireless system is like a cocktail party in which people want to talk to each other simultaneously [5, p14] [18, p668]. This can be done in several ways, without creating confusion. They can either speak at different pitches (analogous to FDMA) or take turns to speak (analogous to TDMA) or speak in different languages (analogous to CDMA). In FDMA, the bandwidth (i.e the band of frequencies) is divided into frequency slots and each user is assigned a different frequency slot for transmission [12, p3]. In TDMA, each user uses the entire bandwidth but is assigned a different timeslot for transmission [1, p365] [21, p13]. Thus, in both TDMA and FDMA, there is a fixed limit on the capacity i.e. a fixed number of users can connect to a base station [1, p401]. However, in CDMA, each user is assigned a unique code for transmission and the capacity is not fixed[1] [1, p365] [21, p15]. The concepts of the three multiple access schemes are shown in Fig. 3.1.

One of the most important advantage of CDMA systems is that there is universal frequency reuse i.e. the same frequency is used in each cell [21, p18]. In contrast, in FDMA and TDMA systems, the frequency is reused in cells which are (sufficiently) spatially separated. Also, as all the cells use the same frequency in CDMA, a user can simultaneously connect to two or more base stations. Another multiple access scheme which can have universal frequency reuse is the Orthogonal Frequency Division Multiple Access (OFDMA), in which each user is

[1]Though the capacity is not fixed, it is limited by the Signal-to-Interference Ratio (SIR) constraints.

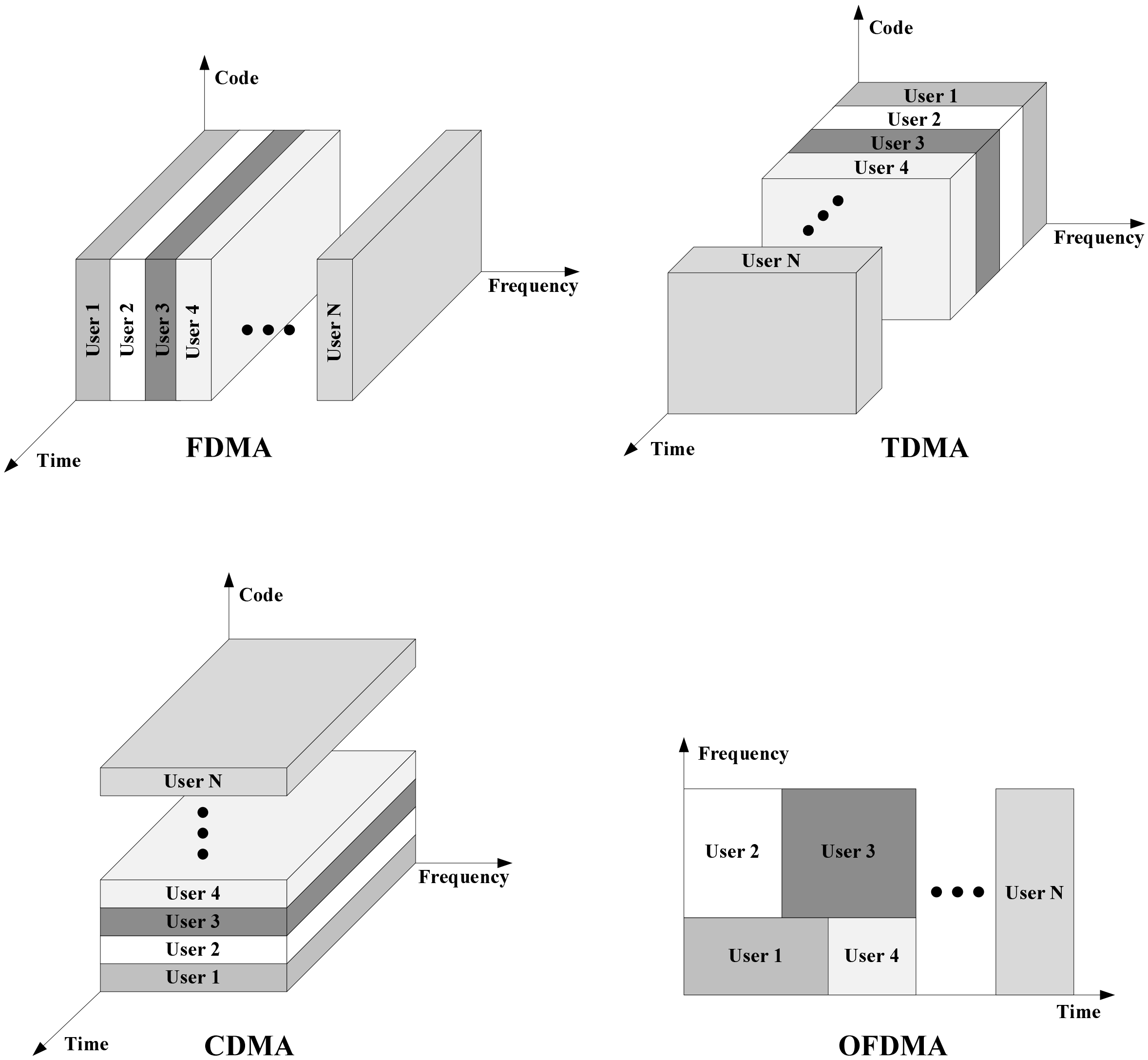


Figure 3.1: Sharing of channel resources in FDMA, TDMA, CDMA and OFDMA.

assigned a subset of the subcarriers as shown in Fig. 3.1 [16, p105] [21, p19]. However, CDMA systems are considered in this thesis because the interference models for CDMA systems are well developed[2] and widely used for system planning.

In this chapter, the fundamentals of CDMA are discussed and the deployment strategies developed (in the literature) for Base Station Placement (BSP) are reviewed. In Section 3.2, the details of CDMA (in particular the operation, handover and power control) are discussed. A literature review of the strategies developed for solving the BSP problem is presented in Section 3.3 and the contributions of this thesis are outlined in Section 3.4. The chapter is summarised in Section 3.5.

3.2 CDMA Fundamentals

CDMA is a multiple access scheme in which each user is assigned a unique codeword and thus, all the users can transmit simultaneously and share the same bandwidth [1, p365] [21, p15]. In Section 3.2.1, the operation of CDMA is discussed focusing on how the transmitter codes and receiver decodes the message. As discussed in Section 2.4, the received message signal is affected by interference and noise. Thus, handover is performed to maintain connectivity of users (while they are moving) and the transmission powers need to be managed to minimise the effect of interference and noise. The handover process and the implementation of power control for CDMA systems are discussed in Sections 3.2.2 and 3.2.3, respectively.

3.2.1 Operation of CDMA

In CDMA, the narrowband message signal is multiplied by a wideband signal called the spreading code before it is transmitted[3] on the carrier channel[4] [5, p15] [17, p458]. As shown in Fig. 3.1, all the users use the same (carrier) frequency and can transmit simultaneously. However, each user is assigned a unique pseudo random codeword which is approximately orthogonal to other codewords and distinguishes it from the other users in the system.

When a user receives a signal (from a base station), it uses its unique codeword to perform a time correlation operation and decode its desired message. In addition to the desired message, the received signal also contains messages for other users which appear as interference (as the codewords of the users are not exactly orthogonal) [21, p16]. The interference increases as the number of users increases and the capacity of the system depends on the total interference

[2] The interference models for OFDMA systems are still being developed [25–27].
[3] The effects of multipath fading are mitigated because the signal is spread over a large spectrum [17, p459].
[4] A carrier channel is a broadband radio frequency channel which carries many code sequences [5, p15].

generated by the users. Thus, CDMA systems are known as 'user-limited' or 'interference-limited' systems [12, p3].

3.2.2 Handover

As discussed in Section 2.4, a user connects to a base station only if the Signal-to-Interference Ratios (SIRs) are above the thresholds, in both the forward and reverse links. As a (connected) mobile user moves away from a base station, the SIR can go below the threshold and handover is performed.

There are two main types of handovers — *hard* and *soft* handovers [17, p67]. In hard handover, the mobile user disconnects from the current base station before connecting to a new base station and thus, it is also referred to as *break-before-make* handover. Soft handover is referred to as *make-before-break* handover as the mobile user connects to the new base station and then disconnects from the current base station [1, p404]. In soft handover, if a base station has multiple sectors, a user can also connect to a different sector of the same base station instead of connecting to a new base station. This is referred to as *softer* handover [5, p17].

Hard handover is performed in FDMA and TDMA systems [5, p17]. The advantage of hard handover is that only one frequency channel is used by the mobile user at any time. On the other hand, CDMA systems perform soft or softer handover and the advantage is that there are no chances of losing a call due to handover failure [1, p404] [17, p67].

3.2.3 Power Control

Power control is necessary for CDMA systems but it is optional for FDMA and TDMA systems [1, p404]. As discussed in Section 2.4, the transmission power is managed using power control schemes in both forward and reverse links.

Forward Link Power Control

The aim of power control on the forward link is to minimise the power of the signal transmitted by the base station ensuring that the received signal power at each user can achieve the required SIR threshold and overcome noise [1, p404] [5, p17] . Power control is implemented by the user, which requests the base station to adjust the forward link signal power to combat interference and noise.

Reverse Link Power Control

If there is no power control on the reverse link and all the users transmit signals with the same power, the near–far problem can occur at a base station i.e. the strongest received signal will

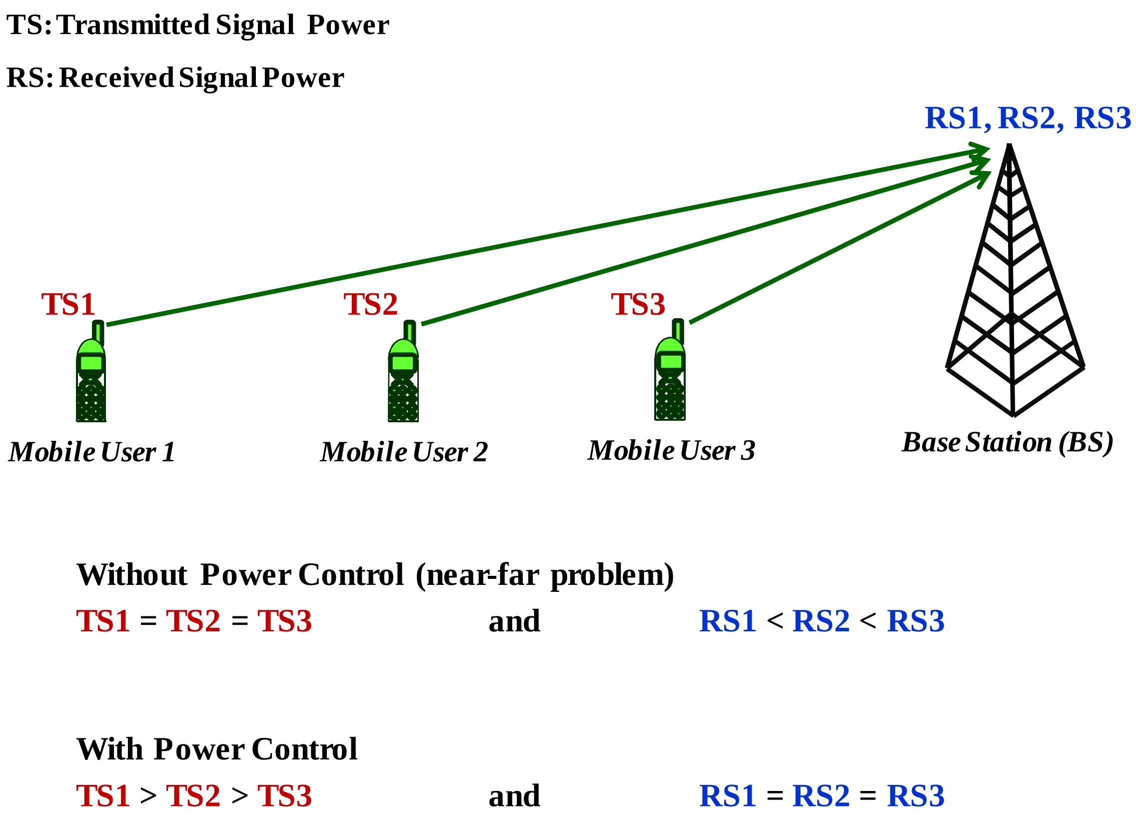


Figure 3.2: An example of near–far problem and reverse link power control. Without power control, the RS3 will be stronger than RS1 and RS2, making it difficult for the base station to detect RS1 and RS2. However, with power control, the three received signals (RS1, RS2 and RS3) will have the same power and will be detected easily.

'capture' the decoder at the base station [17, p458]. This decreases the probability of receiving the weaker signals accurately. Fig. 3.2 shows an example of the near–far problem with three users transmitting to a base station.

Power control is used in reverse link to overcome the near–far problem by ensuring that the signals from all the users are received at the (desired) base station with the same power [17, p458]. This is implemented at the base station by rapidly sampling the received signal powers of each connected user and then sending a power change command to the user [5, p16]. The user responds by adjusting the transmission signal power by a small finite amount[5].

Despite the power control in both links in each cell, the interference due to signals from other adjacent cells cannot be controlled [17, p459]. For example, the power of a user in a cell is controlled by its own (or desired) base station and its transmitted signal is received as

[5]It is impossible to achieve perfect power control as the signal power is adjusted by a finite amount [5, p16].

interference by the other (or undesired) base stations [1, p404]. Though this interference cannot be controlled by the base stations, it can be minimised by careful placement of base stations.

3.3 Deployment Strategies — A Literature Review

The main design criteria for the placement of base stations in FDMA and TDMA systems was coverage maximisation [1,7,28–38] and/or path loss minimisation [37,39]. However, in CDMA systems, the signal power levels and the Signal-to-Interference Ratios (SIRs) are considered as performance measures and included in the recent mathematical models developed for Base Station Placement (BSP) [5, 8, 10, 40–50]. Also, some models developed in the literature include several factors (like traffic variability and multiple classes of services) affecting BSP optimisation and are classified into one (or more) of the following four categories[6]:

1. The optimisation includes *call traffic variability* models i.e. the variability of voice traffic, generally measured in Erlangs.
2. The optimisation includes *user mobility* models i.e. the movement of users and handover.
3. The optimisation includes models for *multiple classes of services with constant bit rates* i.e. the voice traffic and the data traffic with constant bit rates.
4. The optimisation includes models for *packet switched traffic with variable bit rates* i.e. the different traffic distributions to model the variable bit rates (for packet switched systems).

The BSP problem is considered to be an NP-hard optimisation[7] problem [10, 40–43, 51]. Thus, several standard and novel algorithms have been proposed (and compared using case studies) in the literature to solve the BSP problem. The investigations in the literature (i.e. models and algorithms) for solving the BSP problem are discussed in this section and summarised in Table 3.1.

Anderson and McGeehan [52] showed that an optimisation algorithm, Simulated Annealing (SA) can be used for finding the optimal base station locations in an urban micro-cellular environment. The objective of their model is to minimise the difference between the received and the targeted signal strength on a grid of virtual user locations. The study demonstrates that BSP is a combinatorial optimisation problem which can be solved using (optimisation) algorithms like SA. Although SA is shown to be computationally demanding, it may prove to be useful with the continuing advances in computing resources.

[6]In this thesis, the classification is limited to the four categories to include some factors. However, there can be multiple ways to classify the models to include several other factors.

[7]The details of optimisation are discussed in Chapter 4.

Wright *et. al.* [28,29] developed a software package called Wireless System Engineering (WISE) for designing indoor and campus-sized ("microcell") wireless systems. The objective of WISE is to maximise the coverage i.e. the percentage of the building within which the received signal strength is above the defined threshold. The package was written at AT&T Bell Laboratories and uses CAD and optimisation for BSP. The optimisation is performed using a variant of the Nelder-Mead method to find the optimal coordinates for placement of base stations.

Sherali *et. al.* [39] analysed and modelled the problem of placing (a single or multiple) base stations for serving a specified distribution of users. The objective of the study is to minimise the path loss using a nonlinear programming model. Three nonlinear optimisation algorithms, namely, Hooke and Jeeve's methods, Quasi-Newton, and conjugate gradient search procedures are investigated to solve the BSP problem. It is shown that BSP optimisation improves the performance of the system.

Tutschku *et. al.* [53–56] developed an integrated cellular network planning tool (ICEPT) which is one of the earliest tools to include the spatial distribution of the expected teletraffic within the service area of the cellular system. The objective of the tool is to maximise the average Carrier-to-Interference Ratio (CIR) while optimising the covered traffic. The traffic is estimated (considering the geographical and demographical factors) at discrete points, known as demand nodes. The Demand Node Concept (DNC) enabled the formulation of the BSP problem as a Maximal Coverage Location Problem (MCLP), which is well known in economics for solving facility location problems. The earlier version of ICEPT uses Adaptive Base Station Positioning Algorithm (ABPA). However, in [56], a greedy heuristic known as the Set Cover Base Station Positioning Algorithm (SCBPA) is proposed for optimisation.

Neve and Sowerby [57] investigated the suitability of a number of optimisation algorithms including Genetic Algorithms (GA) for solving the complex indoor BSP problem. The objective of their study is to minimise the fraction of a building volume that fails to achieve a defined threshold value of the CIR. It is shown that quantisation effect of an optimisation algorithm can have a significant impact on its performance and thus, the algorithm must be selected (and set up) carefully. It is also shown that SA and GA are suitable for BSP optimisation.

Krishnamachari and Wicker [30,31] analysed the performance of four optimisation algorithms, namely Random Walk (RW), Simulated Annealing (SA), Tabu Search (TS) and Genetic Algorithms (GA), for solving the BSP problem. The objective of the study is to maximise

Investigators	Year (s) of Publication	Models included in Optimisation	Type of Research	Research Outcome	Reference
Anderson and McGeehan	1994		CS	Demonstrated that optimisation algorithms can be used for finding the optimal BSP in micro-cellular systems.	[52]
Wright *et. al.*	1995, 1998		AL, CS	Developed the Wireless System Engineering (WISE) package for indoor BSP.	[28, 29]
Sherali *et. al.*	1996		CS	Demonstrated that optimisation improves the system performance.	[39]
Tutschku *et. al.*	1997, 1998	T	AL, CS	Developed integrated cellular network planning tool (ICEPT).	[53–56]
Neve and Sowerby	1999		CS	Investigated the suitability of several optimisation algorithms for indoor BSP.	[57]
Krishnamachari and Wicker	2000		CS	Compared the performance of four optimisation algorithms.	[30, 31]
Molina *et. al.*	1999, 2000, 2002	T, C	AL, CS	Developed Combinatorial Algorithm for Total optimisation (CAT).	[7, 32–36]
Ji *et. al.*	2002		CS	Developed a model to compare the performance of several optimisation algorithms.	[37]
Fruhwirth and Brisset	2000		AL	Developed the POPULAR (planning for pico-cellular radio) package.	[38]
Lee and Kang	2000	T	CS	Developed a Binary Integer Programming (BIP) model for BSP.	[58]
Amaldi *et. al.*	2002, 2003, 2008	T, C	AL, CS	Proposed discrete optimisation models and algorithms to find the optimal locations and configurations of base stations.	[41–46]

Investigators	Year (s) of Publication	Models included in Optimisation	Type of Research	Research Outcome	Reference
Wong *et. al.*	2003, 2006, 2007	T, C	AL, CS	Developed a unique framework (with mathematical models and optimisation algorithms) for BSP optimisation considering multirate traffic and diversity reception.	[5, 10, 47, 48]
Ngadiman *et. al.*	2005	T	AL, CS	Proposed a novel optimisation algorithm.	[8]
Whitaker *et. al.*	2007	T, C	AL, CS	Demonstrated the effect of including priorities for admission and multiple classes of services.	[49]
Rambally and Maharajh	2009		CS	Demonstrated the importance of mutation operator in optimisation algorithms.	[9]
Khalek *et. al.*	2011	T, C	AL, CS	Developed a novel algorithm by implementing SIR based power controls schemes.	[50]
Pujji *et. al.*	2009, 2010	T, M, C, V	AL, CS	Developed a hybrid algorithm for BSP and investigated the effects of user mobility and packet switched traffic distributions with variable bit rates.	[13–15]

Key for table	
T	The optimisation includes call traffic variability models.
M	The optimisation includes user mobility models.
C	The optimisation includes models for multiple classes of services with constant bit rates.
V	The optimisation includes models for packet switched traffic with variable bit rates.
AL	A new algorithm is reported.
CS	A case study (or studies) is reported.

Table 3.1: A summary of the investigations in the literature for solving BSP problems.

the coverage while selecting the minimum number of base stations (from an initial list of potential locations). It is shown that GA and TS are suitable for solving the BSP problem and GA is particularly scalable to large systems.

Molina *et. al.* [7, 32–36] developed a new algorithm, known as the Combinatorial Algorithm for Total optimisation (CAT) for solving the BSP problem. The objective of the algorithm is to select the minimum number of base stations (out of potential base station locations) required to provide coverage and capacity to a set of users. It is not practical to evaluate all possible combinations of base stations if there are a large number of potential base station locations. Hence, the CAT is implemented by splitting the potential base station locations into smaller groups and evaluating the possible combinations within each group. The best combinations from the groups are merged together in a unique group and the process is repeated until the number of solutions cannot be further reduced. The performance of the CAT is compared to the Greedy Algorithm (GR) and the Genetic Algorithm (GA) and it is shown that the CAT provides better solutions.

The study laid a foundation for optimisation of BSP and was extended to include the factors like traffic variability and multiple classes of services (i.e. voice and data) for BSP optimisation. In [33–35], the optimisation is extended by including non-uniform traffic distribution, priority for admission, delay spread and power control. In [36], optimisation is performed for WCDMA systems with multiple classes of services, using GA and Situation Awareness algorithms, in addition to the CAT.

Ji *et. al.* [37] developed a model to compare the performance of several optimisation algorithms, namely Steepest Descent, BFGS (Quasi-Newton), Simplex, Hooke and Jeeve's method, Rosenbrock, Simulated Annealing (SA) and Genetic Algorithms (GA), to solve the indoor BSP problem. The objective of the model is to maximise the coverage by ensuring that the path loss is less than a defined threshold level. It is shown that Steepest Descent, Simplex, BFGS and Rosenbrock algorithms are unable to achieve 'reasonable' deployments. However, Hook and Jeeve's method, SA and GA provide almost the same 'reasonable' results. It is also shown that a 'suitable' initial guess can significantly reduce the computational time for SA and GA.

Fruhwirth and Brisset [38] developed the POPULAR (planning for pico-cellular radio) package to find the optimal BSP, given the information about the potential base station and user locations and the propagation environment. The objective of the package is to compute the minimal number and locations of base stations (required to provide coverage to all the users) using a unique optimisation model. The attenuation level around each user is estimated using ray-tracing and a polygon is defined around the user. The polygon represents the region in which a base station can be placed to provide service to the user. The intersection of multiple polygons represents the location of a base station to provide service to the multiple users. Similarly, the minimum number and locations of base stations to provide service to all the users are computed.

Lee and Kang [58] formulated the BSP problem using a Binary Integer Programming (BIP) model and solved the problem of serving the user traffic using Tabu Search algorithm. The study considers two types of scenarios — the first is to deploy new base stations in an existing system and the second is to deploy a totally new system (with new base stations). The objective of the study is to minimise the cost (of deploying new base stations) ensuring that the base stations have enough capacity to serve the users and the signal power received at each user is above the defined threshold. Though the study does not consider interference, it emphasises the importance of including the traffic demands and the capacity of base stations. The traffic at the user locations is handled using a similar approach to ICEPT's demand node concept [56]. Depending on the multiple access scheme (i.e. FDMA, TDMA or CDMA), the capacity of a base station is estimated for 2% blocking probability. It is shown that the performance of the proposed Tabu Search is superior to that of the Genetic Algorithm and the CPLEX solver for solving the BSP problem.

Amaldi *et. al.* [41–46] proposed discrete models and algorithms to find the optimal locations and configurations (such as antenna height, tilt and sector orientation) of base stations for UMTS with voice and data traffic. The objective is to find a trade-off between maximising the coverage and minimising the costs. The proposed BIP models consider power control mechanisms and the signal strength levels as well as the SIRs on the forward and reverse links. The optimisation is implemented using customised Tabu Search, which uses the solutions provided by a randomized greedy algorithm. It is shown that the proposed models and algorithms are capable of delivering good solutions for different traffic scenarios.

The study creates realistic optimisation models which consider power levels as well as interference constraints and includes variable voice and data traffic. Though the mobility of users and handover is not included in the model, it is suggested as an extension to the study.

Wong *et. al.* [5,10,47,48] developed a unique framework[8] (with mathematical models and optimisation algorithms) for solving the BSP problem of CDMA systems. The objective of the study is to minimise the number of base stations required to serve the users while satisfying the requirements for coverage, (transmitted and received) powers and (forward and reverse link) SIRs. The optimisation model is formulated using BIP and implemented using a customised Genetic Algorithm (GA). The performance of the GA is compared to the Branch-and-Bound

[8]The details of the framework have been described in Chapters 4 and 5.

(B&B) algorithm and it is shown that although the B&B guarantees to find the optimal solution, its computational time increases significantly as the problem size increases. On the other hand, the GA is shown to be generally effective for solving the BSP problem in 'reasonable' time even when the problem size increases.

Apart from developing comprehensive mathematical models to meet all the (power and interference) constraints for CDMA systems, this study also includes unique BIP models for multirate traffic and diversity reception. The options considered for multirate traffic are Multi-Code (MC) and Varying Spreading Factor (VSF) and diversity reception are Equal Gain Combining (EGC) and Maximal Ratio Combining (MRC). It is shown that multirate traffic and diversity reception influence the signal quality and the BSP required to serve the users. Again, although the influence of user mobility on BSP is not investigated, it is suggested to include mobility profiles and handover strategies as an extension to the study.

Ngadiman *et. al.* [8] proposed a novel optimisation algorithm[9] to solve the BSP problem for CDMA systems with traffic variations. The traffic variability is assumed by considering 'snapshots' of different numbers of fixed users. The objective of the study is to select the minimum number of base station locations (out of the potential locations) required to serve the users, ensuring the SIRs are above the defined thresholds in both forward and reverse links. The proposed optimisation algorithm begins by assuming that all the potential base station locations are active and assigns users to the base stations depending on the path loss. It then deactivates the base stations one by one (reassigning the users every time) as long as the SIR constraints can be met for all the users. The optimal BSP to serve the (variable number of) users is obtained by averaging the results for many iterations. It is suggested that multiple classes of services and user mobility can be included as an extension to the study.

Whitaker *et. al.* [49] investigated the sensitivity of coverage associated with considering 'snapshots' of user traffic for BSP in WCDMA systems. This study focuses on the importance of including the factors (like traffic variability) that can significantly influence BSP and must be analysed for network planning. The objective of the investigation is to demonstrate the effect of including priorities for user admission and multiple classes of services. However, models for user mobility and packet switched traffic (with variable bit rates) are not considered in this study. The algorithm connects the user to the best (i.e. least path loss) base station ensuring the downlink SIR is above the defined threshold. It is shown that admitting the users with greatest-path-loss first is useful and a 'higher data rate user' is satisfied at the expense of multiple 'low data rate users'.

[9]Ngadiman's Algorithm [8] has been implemented in Chapter 5.

Rambally and Maharajh [9] investigated the performance of Genetic Algorithms (by changing the population size and the type of selection) and Tabu Search (by changing the size of candidate list and the tabu tenure) in solving the BSP problem. The objective of the study is to maximise the coverage i.e. the percentage of user locations in the service area which are covered by at least one base station. It is shown that Genetic Algorithms (GA) and Tabu Search (TS) are suitable for BSP and GA performs better than TS if the randomness of the mutation operator is increased.

Khalek *et. al.* [50] developed a novel algorithm for site placement and site selection in UMTS radio planning. In the site placement problem, the objective is to find the optimal locations of base stations to serve a given set of users by minimising the total power expenditure and ensuring that the forward and reverse link SIRs are above the defined thresholds. In the site selection problem, the objective is to select the minimum base stations (from a set of potential base station locations) that satisfy the quality and outage constraints. The optimisation algorithm is implemented by formulating SIR based power control schemes and a nested approach to minimise the number of base stations and other objective functions. Case studies are presented for uniform and non-uniform user distributions with multiple classes of services.

The focus of this thesis is to solve the indoor BSP problem for CDMA systems using mathematical *models* and optimisation *algorithms* and considering the effect of several *factors* on BSP optimisation. In the next section, the contributions of this thesis are discussed in the context of the investigations in the literature.

3.4 Contributions of This Thesis

Since CDMA systems are 'interference-limited', the constraints on SIRs (in both forward and reverse links) along with transmitted and received powers must be considered for optimisation. The unique framework proposed by Wong [5, 10, 47, 48] includes comprehensive mathematical *models* for BSP in CDMA systems to minimise the number of base stations while ensuring that all the (power and interference) constraints are met. The mathematical models used for optimisation in this thesis are similar to those developed by Wong [5, 10, 47, 48] (and are discussed in Chapter 4).

Several standard optimisation algorithms [9, 30, 31, 37, 39, 52, 57, 58] and new optimisation algorithms [5, 8, 10, 28, 29, 38, 40–50, 53–56] have been proposed to solve the BSP problem. In this thesis, the most appropriate *algorithm* for indoor BSP is identified and thus, the contributions of Chapters 5-7 of this thesis are:

- Comparison of the performance of some existing (i.e. standard and new) optimisation algorithms for BSP optimisation; and
- Development of a novel hybrid algorithm and comparison of its performance to the existing algorithms.

In recent years, some published studies have included *factors* such as traffic variability [5, 8, 10, 33–35, 40–50, 53–56, 58] and multiple classes of services [5, 10, 36, 41–46, 48–50] for BSP optimisation. However, to the author's knowledge, models to include the mobility of users and packet switched traffic (with variable bit rates) for BSP optimisation have not been addressed in the literature. In this thesis, four system models are proposed to investigate the effects of traffic variability, user mobility and switching technologies. Also, the BSP is extended to multi-floored buildings and thus, the contributions of Chapters 8-11 of this thesis are:

- Identification of the most suitable system model to include the effects of factors such as call traffic variability, user mobility and call switching technologies on BSP optimisation; and
- Identification of optimal BSP for a multi-floored building using the most suitable system model and considering internal and external base station sites.

Finally, the key conclusions of this thesis are presented in Chapter 12.

3.5 Summary

In this chapter, the fundamentals of CDMA (in particular the operation, handover and power control) have been discussed and a literature review of the strategies developed for solving the Base Station Placement (BSP) problem has been presented.

Code Division Multiple Access (CDMA) is a multiple access scheme in which each user is assigned a unique codeword and all the users can transmit simultaneously and share the same bandwidth. CDMA systems are 'interference-limited' because the capacity depends on the total interference in the system. A base station performs soft or softer handover if the (forward or reverse link) SIRs of a moving (connected) user goes below the defined threshold and power control is implemented (in both forward and reverse links) to minimise the effects of interference and noise.

The deployment strategies developed in the literature have been reviewed and summarised. In CDMA systems, the signal power levels and the (forward and reverse link) SIRs are considered as performance measures and included in the mathematical models developed for BSP. Several standard and new optimisation algorithms have been proposed in the literature to solve the BSP problem and some published studies have included the factors like traffic variability and multiple classes of services for BSP optimisation. However, no studies have been found to include the models for user mobility and packet switching (with variable bit rates) to solve the BSP problem.

In this thesis, the mathematical models used for optimisation are similar to those considered by Wong [5, 10, 47, 48] and are discussed in Chapter 4. In Chapters 5-7, the performance of some existing optimisation algorithms are compared and a novel hybrid algorithm is developed for BSP. In Chapters 8-11, four systems models are proposed to investigate the effects of call traffic variability, user mobility and call switching technologies on BSP optimisation and the BSP problem is extended to multi-floored buildings.

Chapter 4

Optimisation and Wireless System Modelling

4.1 Introduction

Optimisation is the process of solving a design problem by choosing the best option (the optimal solution) from a number of available alternatives [59, p3]. Increased competition and demand in industry and business drives the desire for optimal solutions, which can maximise profit [60, p1]. For example, engineers responsible for deploying base stations in wireless communication systems, need to choose the best locations (out of all possible locations) for maximising the quality and capacity while minimising the interference and cost of the system [10, 47, 61].

Although some problems are simple and can be solved manually using personal experience and judgement, many practical problems cannot be solved this way and require an efficient numerical[1] optimisation process. Today, numerical optimisation is used to solve problems involving decision making in many disciplines including engineering, financial planning, mathematics and computer science. The focus of this thesis is the indoor Base Station Placement (BSP) problem in which the goal is to find the optimal number and locations of base stations required to serve the users. The purpose of this chapter is to describe the fundamental concepts of optimisation and apply these concepts to develop mathematical models for BSP optimisation. Section 4.2 presents an overview of optimisation considering it as a number of distinct stages which will be used in the formulation of the BSP problem. In Section 4.3, optimisation is performed for the BSP problem and models for BSP optimisation are developed which will be used throughout this thesis. The chapter is summarised in Section 4.4.

[1] In the context of this thesis, numerical optimisation refers to the optimisation performed using a computer.

4.2 Optimisation — An Overview

The word optimum, meaning 'best', refers to either a maximum or minimum, and optimisation is defined as the process of maximising or minimising a desired objective function while satisfying a given set of constraints [5, p31] [59, p3] [62, p1]. It has been suggested that the optimisation of problems, such as the placement of base stations in wireless communication systems, should be tackled in stages [5, p36]. In this thesis, optimisation is performed in the four stages outlined in Fig. 4.1. The problem is defined in the first stage and then quantified in the second stage. In the third stage, an appropriate algorithm is identified and applied to find the solution which is finally implemented in the fourth stage.

4.2.1 Optimisation Stage I: Define Problem

The first stage of optimisation, as shown in Fig. 4.1, is to define the problem. The problem definition describes the existing system and the desired goal. For example, in this thesis, the Base Station Placement (BSP) problem is solved which can be defined, in simple words[2], as 'find the optimal number and locations of base stations required to serve a given set of users under a set of specified constraints'.

The problem definition is a way of qualitatively (i.e. in words) describing the features of an optimal system without including a quantitative (i.e. mathematical) analysis. However, the definition provides all the information required to formulate a quantitative analysis of the problem (in the next stage of optimisation).

4.2.2 Optimisation Stage II: Quantify Problem

As shown in Fig. 4.1, after the problem is defined, it is quantified in the second stage of optimisation. The quantification of the problem is performed by defining the different quantification components (*decision variables*, *constraints* and *objective function*) and modelling the components mathematically [5, pp33-36] [63, p6] [64, p16] [65, pp936-937].

Decision Variables

Decision variables are used to quantify the decisions that need to be taken to find a solution to an optimisation problem. For example, to solve the BSP problem for a wireless communication system, decision variables might represent the number and physical locations of the base stations to be deployed.

[2]The details of the BSP problem definition are given in Section 4.3.1.

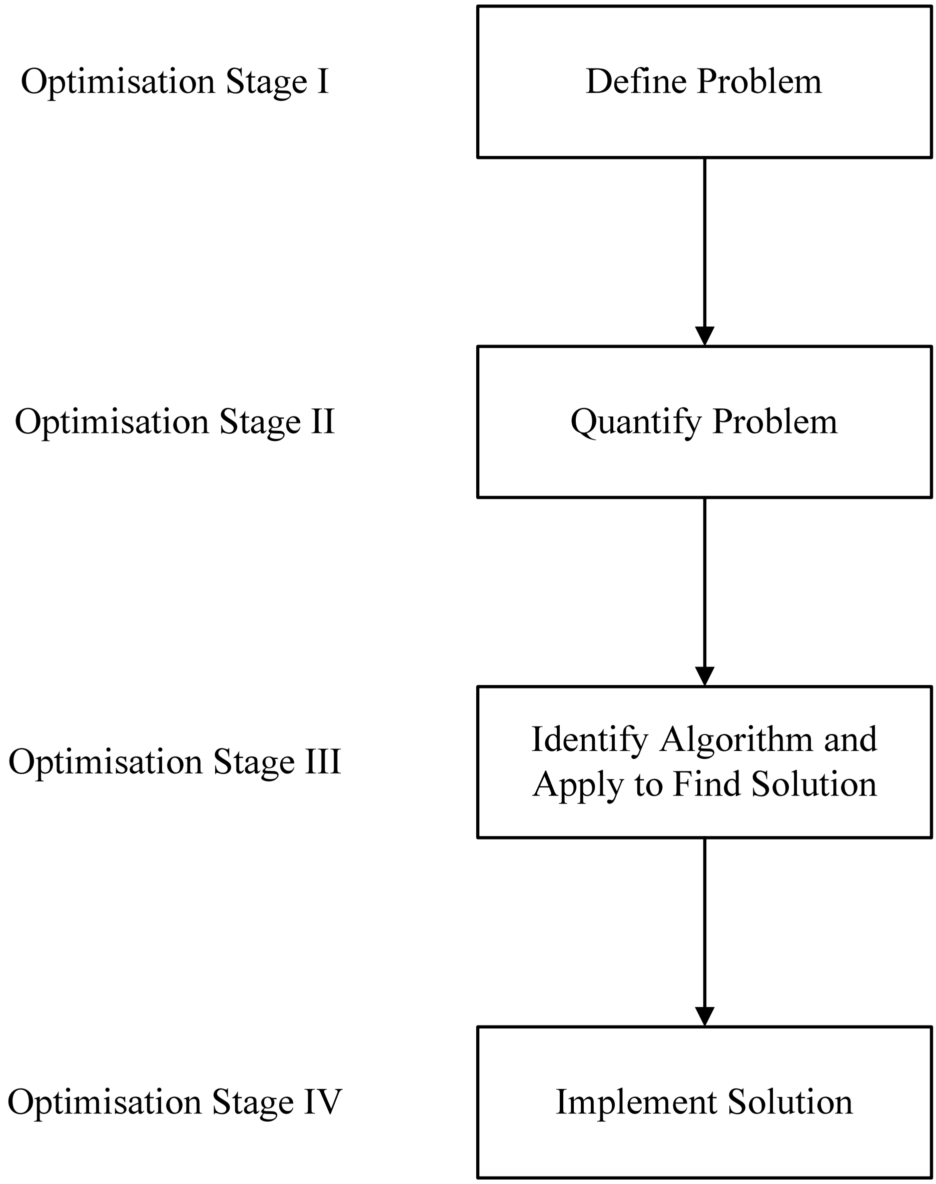


Figure 4.1: Fundamental stages of solving a problem using optimisation.

Constraints

These are the essential conditions that the solution must satisfy and are usually expressed as inequalities. For example, in BSP optimisation, a common constraint is that the transmission power of a user, P_{tu} cannot exceed a predefined maximum transmission power value, P_{max} and it can be expressed as,

$$P_{tu} \leq P_{max}.$$

In practice, there are many other constraints that need to be taken into account while designing wireless communication systems including the minimum Signal-to-Interference Ratio (SIR) and the minimum signal power required at the receiver.

Objective Function

The objective function is the mathematical function that needs to be optimised (either maximised or minimised) and is expressed in terms of the decision variables. For example, in BSP optimisation, the objective can be to minimise the number of base stations, N_{bs} required to serve the users while satisfying the constraints, and the objective function can be expressed as,

$$\text{minimise}(N_{bs}).$$

The aim of Stage II of optimisation is to quantify the problem (by finding the different components[3]) using the problem definition from Stage I. The overall goal of optimisation is to solve the problem by finding the values of the decision variables to maximise or minimise the objective function, subject to the given constraints. This goal can be achieved by the application of algorithms.

4.2.3 Optimisation Stage III: Identify Algorithm and Apply to Find Solution

As shown in Fig. 4.1, the third stage of optimisation is to identify an appropriate algorithm and apply it to find the solution. An algorithm is defined as a procedure for solving a problem [66, p3]. The effectiveness of an algorithm is judged by its *accuracy* (or the correctness of solution) and *efficiency* (or the computation time of execution). The identification of the algorithm is based on the type of problem to be solved. A problem can be either continuous (i.e. decision

[3]The quantification components (decision variables, constraints and objective function) used for BSP optimisation in this thesis are defined in Section 4.3.2.

variables can have continuous values like temperature, time, height) or discrete (i.e. decision variables can have only integer values like number of people, vehicles, base stations). In this thesis, the focus is on the BSP problem which is a discrete combinatorial problem[4].

In Fig. 4.2, the classification of various algorithms for solving discrete combinatorial problems, namely *brute force search* and *optimisation* algorithms, are shown in the form of a Venn diagram. The ***Brute Force/ Exhaustive Search*** algorithm is implemented by generating all possible solutions, then finding those which satisfy the constraints and finally selecting the best solution [66, p113]. This algorithm can be applied to a wide variety of problems and guarantees to find the best solution because it searches exhaustively through all possible solutions [66, p98]. However, its application is limited to solving small sized problems because its computational time increases dramatically as the size of the problem (and the number of possible solutions) increases [62, p17] [66, p118].

As shown in Fig. 4.2, the main class of algorithms to solve combinatorial problems is ***Optimisation*** algorithms. These algorithms have been developed for solving practical problems intelligently (without checking every possible solution) and efficiently [5]. In Fig. 4.2, the two sub classes of *optimisation* algorithms, namely *deterministic* and *heuristic* [67, p22], are also shown.

- ***Deterministic*** algorithms are predictable and always produce the same output (passing through the same decisions at every step) for a particular input [67, p552]. Some examples are *state space search*, *branch and bound* and *algebraic geometry* algorithms [67, p23]. These algorithms generally find the best solution successfully but can have high computation time which increases rapidly as the size of the problem increases [5, p89] [48].

- ***Heuristic*** algorithms are based on experiment, trial-and-error or evaluation of feedback [66, p386]. They are iterative and adjustment in each iteration is performed using the feedback from the previous iteration. They are generally faster than other algorithms but they do not guarantee the best or indeed any solution. However, they can be used to provide good approximate solutions and initial estimates. A popular example is the *greedy search* algorithm. ***Probabilistic*** algorithms are a class of *Heuristic* algorithms (as shown in Fig. 4.2) which use the results of a random process in at least one of the steps of the algorithm and thus, may not always produce the same output for a particular input [67, p552]. Some examples are *genetic*, *tabu search* and *simulated annealing* algorithms [67, p23].

[4]The discrete combinatorial problems are the problems where the best solution is found from a set of discrete possible solutions [63, p151] [66, p22].

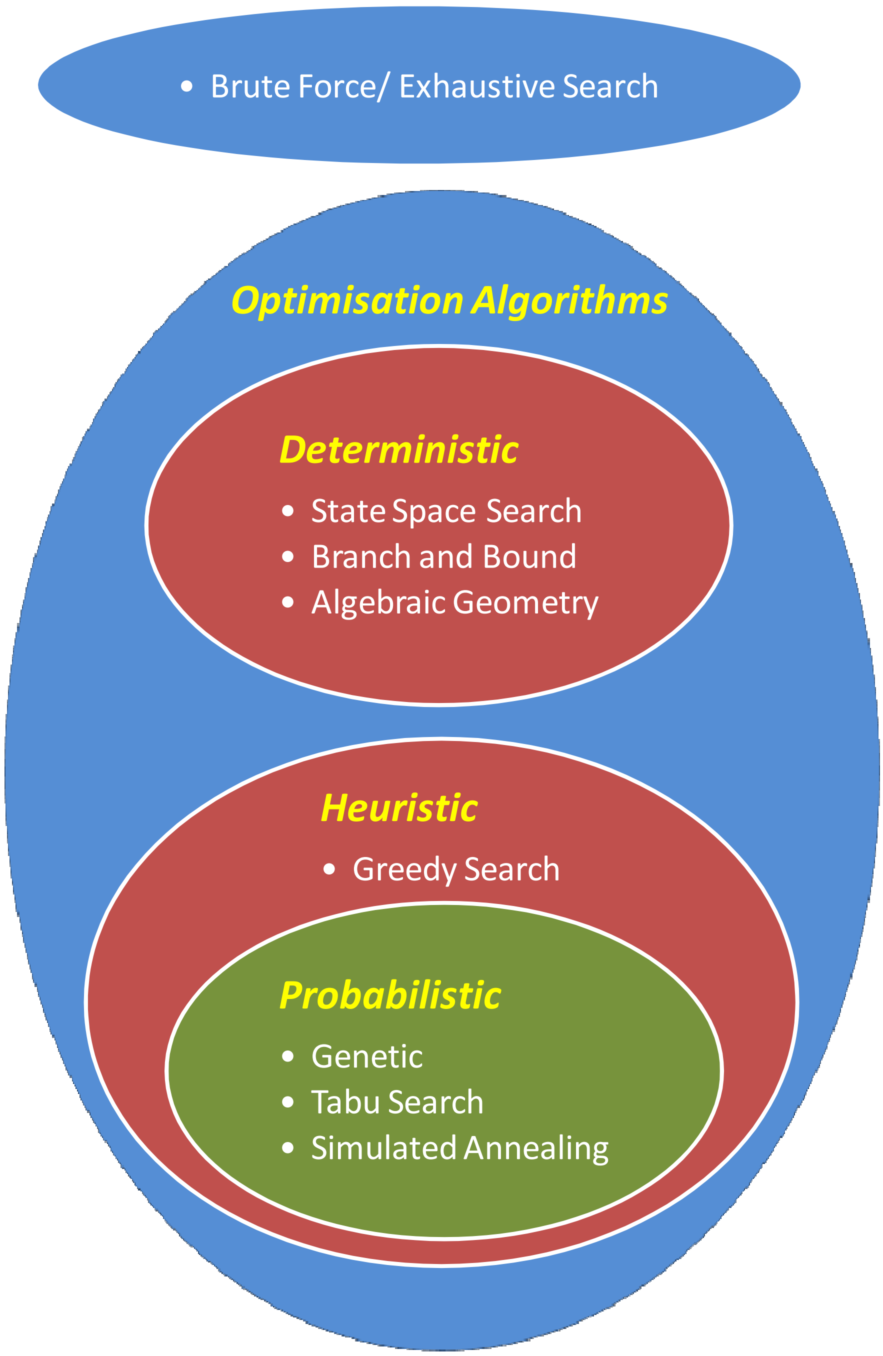


Figure 4.2: Venn diagram of the algorithms for solving combinatorial problems. In this figure, italics are used to represent a class of algorithm and bullets are used to represent the actual algorithms.

In Chapter 5, a number of these standard (existing[5]) algorithms have been implemented to solve the BSP problem and their effectiveness is compared using a case study. The BSP problem is considered to be a NP-hard[6] combinatorial problem and therefore is challenging to solve using the standard algorithms [10, 40–43, 51]. Some researchers have developed ***Hybrid*** algorithms which can combine the advantages of the standard algorithms to find a solution for NP-hard problems [64, p2]. In Chapter 6, a *hybrid* algorithm has been developed to solve the BSP problem and its effectiveness is compared to the existing algorithms using the case study from Chapter 5.

The problems solved by algorithms can have a finite set of possible solutions (*feasible solutions*) but they usually have only one best solution (the *optimal solution*). *Feasible solutions* are the solutions that satisfy all the constraints of the problem [5, p34] [65, p942]. The *optimal solution* is a *feasible solution* that provides the optimal (minimum or maximum) value for the objective function.

4.2.4 Optimisation Stage IV: Implement Solution

The fourth and final stage of solving a problem using optimisation, as shown in Fig. 4.1, is the practical implementation of the optimal solution (found by the application of the appropriate algorithm in the third stage of optimisation).

As the four stages of optimisation have been discussed, it is now appropriate to consider how these stages of optimisation can be applied to solve the BSP problem.

4.3 Optimisation for Base Station Placement (BSP)

As discussed in Chapter 1, indoor wireless communication systems are becoming increasingly popular and optimal deployment of the systems is critical for their efficient functioning [4, p72] [10] [11, p316]. The aim of this thesis is to solve the Base Station Placement (BSP) problem for indoor systems using mathematical *models* and optimisation *algorithms* and considering the effect of several *factors*.

In this section, two (out of four) stages of optimisation (shown in Fig. 4.1 and described in Section 4.2) are applied to develop mathematical *models* for BSP optimisation which have been used throughout this thesis to solve the BSP problem. Thus, the problem is defined (i.e. Stage I) and quantified (i.e. Stage II) in this chapter while an appropriate *algorithm* is identified and applied[7] (i.e. Stage III) in Chapters 5-7 and Chapters 7-11, respectively.

[5] The existing algorithms are the algorithms which have been proposed in the past to solve the BSP problem.
[6] A class of problems which cannot be solved in polynomial time [66, pp386].
[7] The algorithm is applied to investigate the effect of several *factors*.

4.3.1 Optimisation Stage I: BSP Problem Definition

The aim of BSP optimisation is to find the optimal number and locations of base stations to serve the given set of users in an indoor environment under a set of specified constraints (using the defined Call Admission Control (CAC) strategy and achieving the desired Grade of Service (GoS)). In this thesis, the BSP problem has been defined using the *potential base station sites and user locations*, *path loss estimation*, *CAC strategy* and *GoS*.

Potential Base Station Sites and User Locations

The optimal solution (number and locations of base stations) will depend on the number of users requiring service or the expected traffic conditions. In this thesis, it is assumed that there is a finite number of potential user locations, N_u requiring service [5, pp71-72] [48]. It is also assumed that there is a finite number of potential base station sites[8], N_{bs} and the optimal base stations are selected as a subset of the full list of potential sites.

As an example, the physical layout of a floor in the School of Engineering Tower at The University of Auckland is shown in Fig. 4.3. The floor measures 18.5m $\times$ 18.5m and has a centrally located concrete services core (containing the lifts and stairwell) which is surrounded by a corridor. The corridor is in turn surrounded by offices. As shown in the figure, there are 54 potential user locations (indicated by ○) and 24 potential base station sites (indicated by +). Thus, in this case, $N_u = 54$ and $N_{bs} = 24$ and the optimal base station sites will be selected from the 24 potential sites.

Path Loss Estimation

Path loss estimates are required to predict the strengths of signals and interferences at a receiver which are, in turn, used to determine the Signal-to-Interference Ratio (SIR). Free space path loss estimates are used in Chapters 5-6 for simplicity and comparison of the algorithms. As discussed in Chapter 2, the propagation environments can cause significant variations in signal strengths and thus, in Chapters 7-11, the path loss estimates are based on the real experimental measurements[9] carried out in the actual buildings.

[8]The number of potential base stations considered is finite because installation and maintenance constraints will naturally limit the locations where base stations can be physically deployed.

[9]Appendix A describes how the measurements were performed [5].

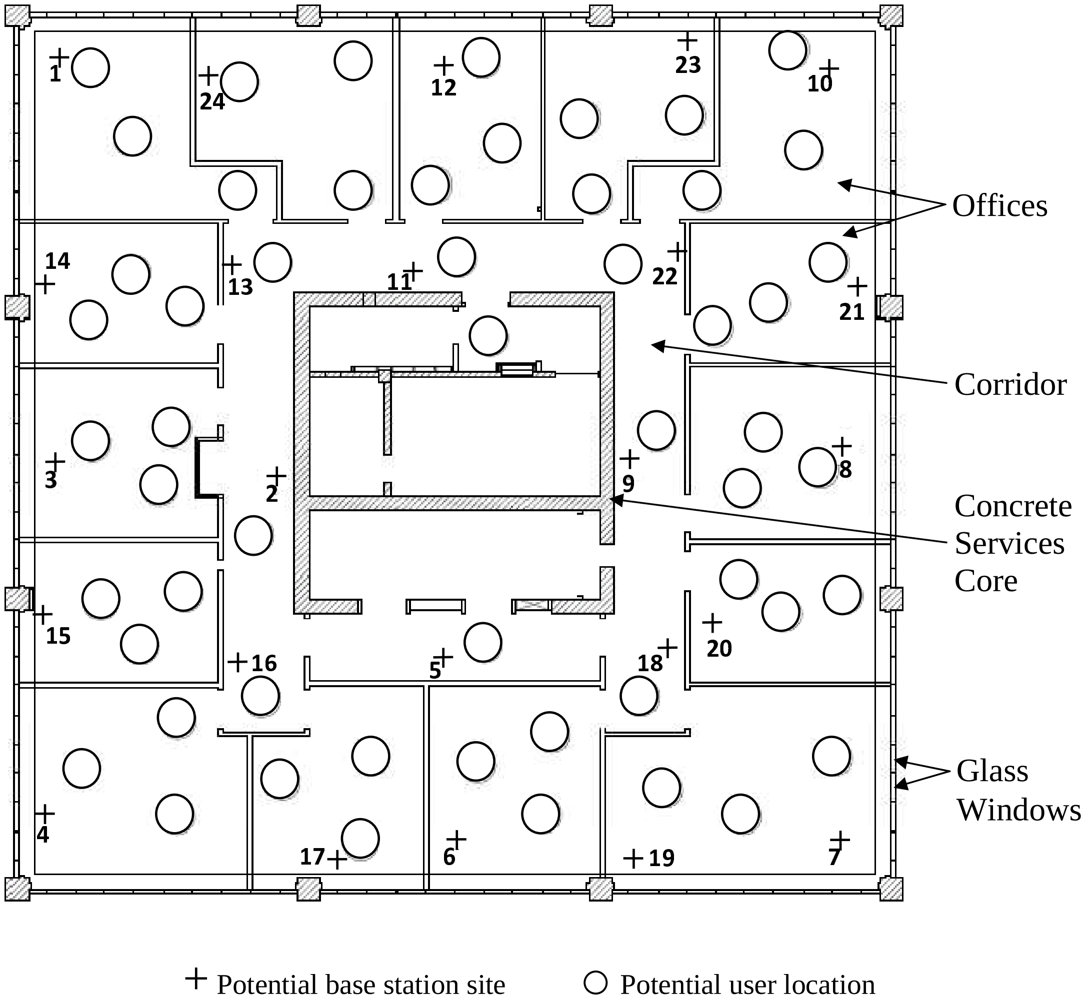


Figure 4.3: Example floor layout (18.5m × 18.5m).

Call Admission Control (CAC) Strategy

Call Admission Control (CAC) strategy is the process by which the arriving calls (new or handover calls) are managed at the base station [16, p131]. The CAC strategy decides whether to connect or block a call based on predefined criteria.

The CDMA CAC strategy is used in this thesis[10]. The amount of interference (not the number of channels) limits the number of connected calls in a CDMA system and it is assumed that there are sufficient orthogonal codes to supply all the users in the system [5, p71]. The interference in the system is due to the transmissions between the base stations and the users while the system noise is not considered explicitly in this study.

[10] As mentioned in Chapter 3, the CDMA CAC strategy is used because the interference models for CDMA systems are well developed and widely used for radio planning [8, 10, 42, 43, 48, 68] whereas the interference models for OFDMA systems are still being developed [25–27].

In Fig. 4.4, a simplified CAC flowchart for CDMA systems shows the five main conditions that are checked before a call is connected [5, pp71-73] [69, pp109-125]. When a call connection is requested at the base station, it is checked if the signal power received by the user is at least Q_f (forward link SIR threshold) times stronger than the total interference signal powers on the forward link (*Condition 1*). Similarly, it is checked if the signal power received by the base station is at least Q_r (reverse link SIR threshold) times stronger than the total interference signal powers on the reverse link (*Condition 2*). In other words, the forward and reverse link SIRs must be greater than or equal to the Q_f and Q_r, respectively. As shown in Fig. 4.4, if any of the SIR requirements are not fulfilled, the call is blocked. If both the requirements are fulfilled, the next set of conditions is considered. It is checked that the power of the signal arriving at a user (after path loss and processing gain) is above a minimum level, P_{min} (*Condition 3*) and the user transmission power (assuming perfect power control on the reverse link) does not exceed a maximum level, P_{max} (*Condition 4*). Again (as shown in Fig. 4.4), if any of the conditions are not fulfilled, the call is blocked. If both the conditions are fulfilled, the base station checks that the admission of the user will not sacrifice any of the existing connections (*Condition 5*). The base station checks this by estimating the interference increase from the call connection in the forward and reverse link directions. The call is blocked if it causes excessive interference on either the forward or the reverse link otherwise it is connected to the base station.

In this thesis, CDMA systems with an operating frequency of 1.8GHz are considered because the path loss measurements were carried out in the buildings at this standard CDMA frequency [5, 10, 47, 48]. As in a previous study [5], the processing gain (G_p) is chosen to be 128. The SIR thresholds for the forward link (Q_f) and the reverse link (Q_r) have been set to 7 (8.45dB) and 5 (7dB), respectively [5]. It is also assumed that there is perfect power control on the reverse link and transmissions from the different users arrive at their desired base station with the same strength of 1nW. The transmission power of a base station for each user is set to 1mW and the total power is determined by the number of users connecting to the base station.

Grade of Service (GoS)

Grade of Service (GoS) is the measure of performance required by the system to achieve efficient service [17, p78] [70, p155] [71]. GoS (4.1) is the percentage of calls that are lost (new calls blocked and existing calls dropped) out of the total number of calls [4, p223] [23, p361] [72, p242].

$$\text{GoS } (\%) = \frac{\text{Number of lost calls}}{\text{Total number of calls}} \times 100 \tag{4.1}$$

A wireless communication system must be designed to achieve the desired GoS for the ‘busy hour’ (when the maximum number of users is served) [4, p223] [23, p249]. Normally, it is

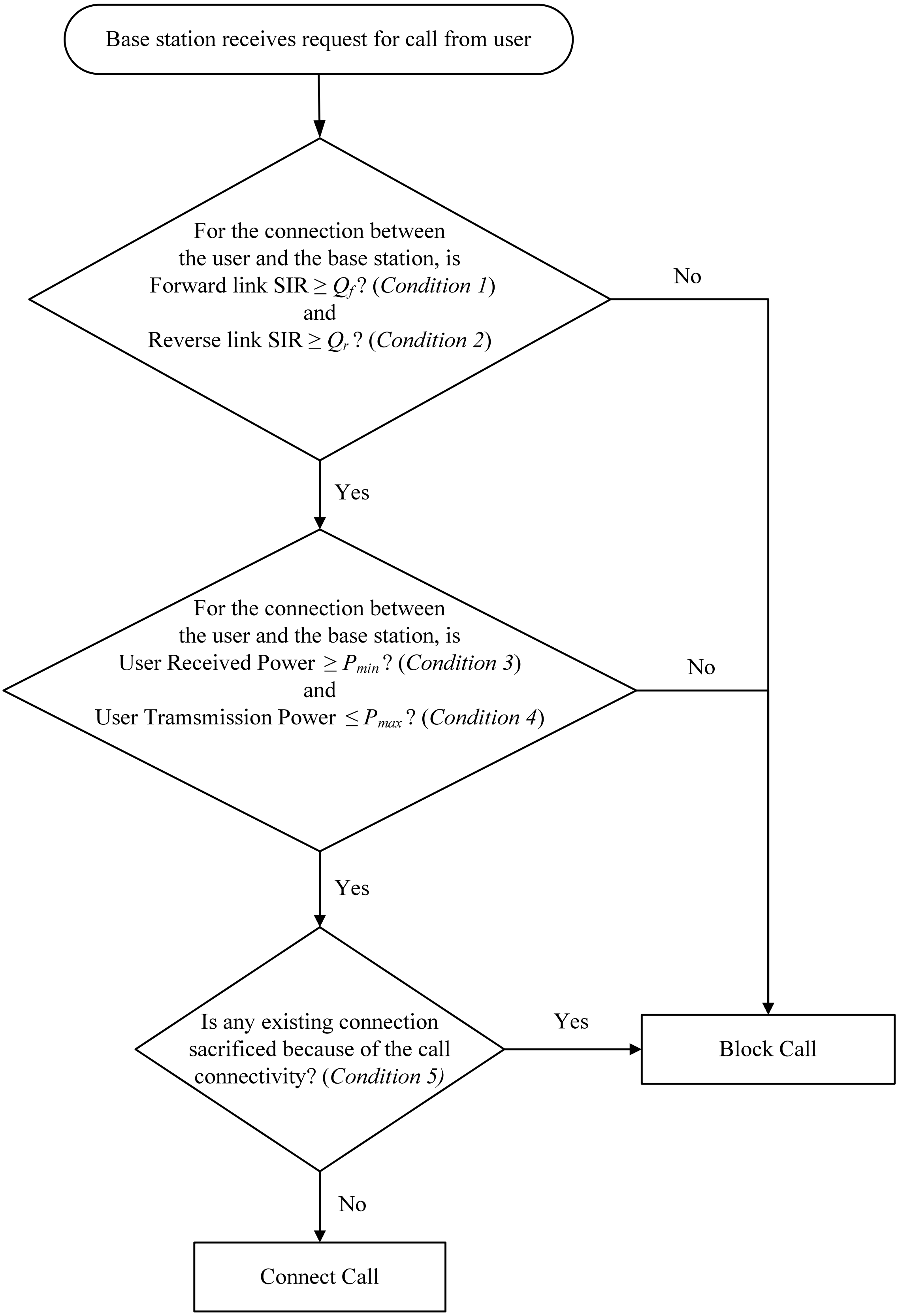


Figure 4.4: CDMA Call Admission Control (CAC) strategy flowchart.

not possible to provide service economically to 100% of the users even with a dense layout of base stations due to the nature of radio wave propagation inside buildings [4, pp187-188]. The GoS adopted in this thesis is '2%', i.e. at most 2% of the total calls are lost (either blocked or dropped) and at least 98% of the calls are connected to a base station with the desired level of SIR [4, pp187-188] [68].

Now that the BSP problem has been defined, the second stage of optimisation (as shown in Fig. 4.1) is to quantify the BSP problem.

4.3.2 Optimisation Stage II: BSP Problem Quantification

The BSP problem is quantified by defining and modelling the quantification components (decision variables, constraints and objective function) based on the BSP problem definition discussed in Section 4.3.1.

Decision Variables

In this thesis, the decision variables correspond to the locations of base stations and connection of users and base stations. The decision variables chosen are Y_b (whether a base station is to be deployed at a potential site) and X_{bu} (whether a link is to be established from this potential base station site to a user) [10, 47, 48, 61]. Therefore,

$Y_b = 1(0)$ if a base station is (is not) deployed at potential site b; and

$X_{bu} = 1(0)$ if a link is (is not) established between base station b and user location u.

where $b = 1, 2, 3...N_{bs}$ and $u = 1, 2, 3...N_u$ and N_{bs} and N_u are the total number of potential base station sites and users (requiring service), respectively.

Constraints

The constraints for the BSP problem are based on the CAC strategy and GoS requirement defined in Section 4.3.1. According to the five conditions in the CDMA CAC strategy flowchart (shown in Fig. 4.4), the typical measures of performance for CDMA systems are the SIRs (on both the forward and reverse links) and the signal levels (transmitted and received by a user). Thus, the specific constraints for BSP optimisation based on the CDMA CAC strategy are [5, pp71-73] [10] [47] [48] [69, pp109-125]:

1. When connecting a user to a base station, the signal power received by the user (after accounting for the effects of path loss and processing gain) is required to be Q_f (forward link SIR threshold) times stronger than the sum of the interference signal powers[11] on the

[11] Interference is due to the other users connected to the same base station and all the users connected to other base stations.

forward link. Therefore, the forward link SIR must be greater than or equal to the Q_f (4.2) (*Condition 1* in Fig. 4.4),

$$\frac{\text{Received user signal power}}{\sum \text{Interference}} \geq Q_f. \tag{4.2}$$

2. The signal power arriving at a base station from each of its users is required to be Q_r (reverse link SIR threshold) times stronger than the total reverse link interference. Therefore, the reverse link SIR must be greater than or equal to Q_r (4.3) (*Condition 2* in Fig. 4.4),

$$\frac{\text{Received base station signal power}}{\sum \text{Interference}} \geq Q_r. \tag{4.3}$$

3. The power of the signal received at a user, P_{ru} (after path loss and processing gain) must be above a defined minimum level, P_{min} (4.4) (*Condition 3* in Fig. 4.4),

$$P_{ru} \geq P_{min}, \quad u = 1, 2, 3...N_u. \tag{4.4}$$

4. The transmission power for a user, P_{tu} (assuming perfect power control on the reverse link) must not exceed a defined maximum level, P_{max} (4.5) (*Condition 4* in Fig. 4.4),

$$P_{tu} \leq P_{max}, \quad u = 1, 2, 3...N_u. \tag{4.5}$$

5. Before connecting a new user to a base station, it is checked that none of the existing connections will be sacrificed because of the interference created by the new connection (*Condition 5* in Fig. 4.4).

Furthermore, the additional constraint based on the GoS (discussed in Section 4.3.1) [4, pp.187–188] [68] is:

6. At least 98% of the users can connect to a base station with the desired level of SIR (4.6).

$$\text{Grade of Service (GoS)} \leq 2\% \tag{4.6}$$

Therefore, a total of six constraints are considered for BSP optimisation in this thesis which are based on the CDMA CAC strategy and GoS.

Objective Function

The aim of BSP optimisation is to optimise (minimise) the number of base stations required to serve the given set of users (ensuring the given constraints are met) [10, 47, 48]. Formally,

$$\text{minimise}(\sum_{b=1}^{N_{bs}} Y_b). \tag{4.7}$$

where $Y_b = 1(0)$ if a base station is (is not) deployed at potential site b.

Now, the BSP problem is defined and quantified and the next stage of optimisation (as shown in Fig. 4.1) is to identify and apply algorithms to find the optimal solution. In Chapters 5 and 6, several algorithms are implemented and a hybrid algorithm is developed to identify the most appropriate algorithm for the optimisation of the indoor BSP problem.

4.4 Summary

In this chapter, the concept of optimisation and the stages of solving a design problem using optimisation have been discussed and applied to the indoor Base Station Placement (BSP) problem.

Optimisation is defined as the process of maximising or minimising a desired objective function while satisfying a given set of constraints. There are four fundamental stages in solving a problem using optimisation, namely i) define problem, ii) quantify problem, iii) identify algorithm and apply to find solution and iv) implement solution. The problem is defined in the first stage and the desired goal is identified. In the second stage of optimisation, the problem definition is used to quantify the problem by modelling the different components (decision variables, constraints and objective function).

The third stage of optimisation is to identify and apply an appropriate algorithm to find the optimal solution. The algorithms for solving combinatorial problems are broadly classified as brute force search and optimisation (deterministic and heuristic) algorithms. The BSP problem is generally considered to be a NP-hard combinatorial problem which is difficult to solve using standard algorithms. Some researchers have developed hybrid algorithms to find solutions to NP-hard problems. The algorithms aim to find the optimal solution (to the problem) which is implemented in the fourth and final stage of optimisation.

After the stages of optimisation were described, the first and second stages have been applied to model the BSP problem in this chapter. The aim of BSP optimisation is to find the minimum number and locations of base stations to serve the given set of users in an indoor environment using the defined Call Admission Control (CAC) strategy and achieving the desired Grade of Service (GoS). In the first stage, the problem definition is outlined using the number of potential base station sites and user locations, path loss estimation, CAC strategy and desired GoS. In this thesis, it is assumed that there are only a finite number of potential base station sites and user locations. The optimal base station sites are selected as a subset of the full list of potential sites. The path loss is estimated using free space propagation in Chapters 5-6 and using the real experimental measurements carried out in the actual buildings in Chapters 7-11. The CDMA CAC strategy is used in this thesis where the amount of interference limits the number of calls connected. The GoS adopted in this thesis is 2% i.e. at least 98% of the users can connect to a base station with the desired level of Signal-to-Interference Ratio (SIR).

In the second stage, the problem is quantified by modelling the quantification components (decision variables, constraints and objective function). The decision variables correspond to whether a base station is to be deployed at a potential base station site and whether a link is to be established from this potential site to a user. The constraints are modelled based on the defined CAC strategy and the required GoS. The objective of the optimisation is to minimise the number of base stations required to serve the given set of users ensuring all the constraints are met.

In Chapters 5 and 6, algorithms are applied to the BSP problem modelled in this chapter, to identify the most appropriate algorithm for BSP optimisation. In Chapter 5, some existing algorithms are implemented and compared (using a case study) and in Chapter 6, a hybrid algorithm is developed and compared to the existing algorithms (using the case study).

Chapter 5

Existing Algorithms for Base Station Placement — A Comparison

5.1 Introduction

Base Station Placement (BSP), investigated in this thesis, is a discrete combinatorial optimisation problem which should be tackled in stages [5, p36]. Therefore, in Chapter 4, the four fundamental stages of solving a problem using optimisation (shown in Fig. 4.1), namely i) define the problem, ii) quantify the problem, iii) identify an appropriate algorithm and apply it to find a solution and finally iv) implement the solution, were discussed. Then, stages (i) and (ii) were applied to define[1] and quantify[2] the BSP problem (for indoor wireless communication systems).

The goal of this chapter is to apply the stage (iii) of the optimisation process to identify an appropriate algorithm (solution method) which can be applied to solve the indoor BSP problem. The choice of algorithm is based on the type of problem to be solved [66, pp19-23]. In this chapter, four existing[3] algorithms relevant to solving the indoor BSP problem (namely, the *Brute Force Search, Genetic*, *Greedy* and *Ngadiman* algorithms) are described and their implementation is discussed in Section 5.2. In Section 5.3, the four algorithms are compared[4] using a case study (Case Study 1) to identify which (if any) is the most appropriate algorithm for solving the indoor BSP problem. The chapter is summarised in Section 5.4.

[1]The BSP problem is defined as 'find the optimal number and locations of base stations (out of the potential base station sites) required to serve a given set of users under a set of specified constraints'.

[2]The BSP problem is quantified by modelling the quantification components (*decision variables*, *constraints* and *objective function*) mathematically.

[3]The existing algorithms are the algorithms which have been proposed in the past to solve the BSP problem.

[4]The algorithms are compared in terms of *accuracy* (or the correctness of solution) and *efficiency* (or the speed of execution) [66, p3].

5.2 Existing Algorithms for Base Station Placement (BSP)

As discussed in Chapter 3, researchers have proposed a number of algorithms to find the optimal solution (i.e. the BSP combination which satisfies all the constraints and has the minimum number of base stations) for the BSP problem. A subset of the proposed algorithms which have been identified as being relevant to the indoor BSP problem are:

(a) Brute Force Search (*BFS*)

(b) Genetic Algorithm (*GEN*) [7, 9, 10, 13, 47, 48, 57, 73, 74].

(c) Greedy Algorithm (*GRE*) [7, 75, 76]; and

(d) Ngadiman's Algorithm (*NGA*) [8].

In this section, an overview of the four algorithms (*BFS*, *GRE*, *NGA* and *GEN)* is presented by describing how the algorithms have been implemented in this thesis.

5.2.1 The *Brute Force/Exhaustive Search* (*BFS*)

The *Brute Force/Exhaustive Search* (*BFS*) algorithm searches all possible solutions to select the best solution [66, p113]. The flow diagram for the implementation of *BFS* is shown in Fig. 5.1. First, the algorithm **generates** all possible BSP combinations by selecting two base stations out of the total number of potential base station sites. Then, it **evaluates** the call failure rate[5] of the generated combinations and **checks** if an acceptable solution (with call failure rate $\leq 2\%$) is found. If an acceptable solution is found, the search stops otherwise it continues by selecting three (one more than two) base stations. The process of generation, evaluation and checking is repeated for all BSP combinations of three base stations. If an acceptable solution is found, the search stops otherwise it continues by increasing the number of selected base stations by one and repeating the process until an acceptable solution is found.

BFS guarantees to find the optimal solution because it searches exhaustively through all possible solutions [66, p119]. However its computational time (which is proportional to the number of possible solutions) increases dramatically as the size of the problem increases [66, p118] [7] [62, p17] . Although *BFS* is a simple algorithm which can be applied to a wide variety of problems, it is generally suitable for either solving small-sized problems or judging the *accuracy* (or the correctness of solution) of the other algorithms [66, p98] [77]. In this thesis, *BFS* is implemented to benchmark the *accuracy* of the BSP solutions found using the other algorithms.

[5]The call failure rate is evaluated by allocating the users to the base stations using the CAC strategy (described in Section 4.4). The rate is averaged over a number of trials (as described in Section 5.3).

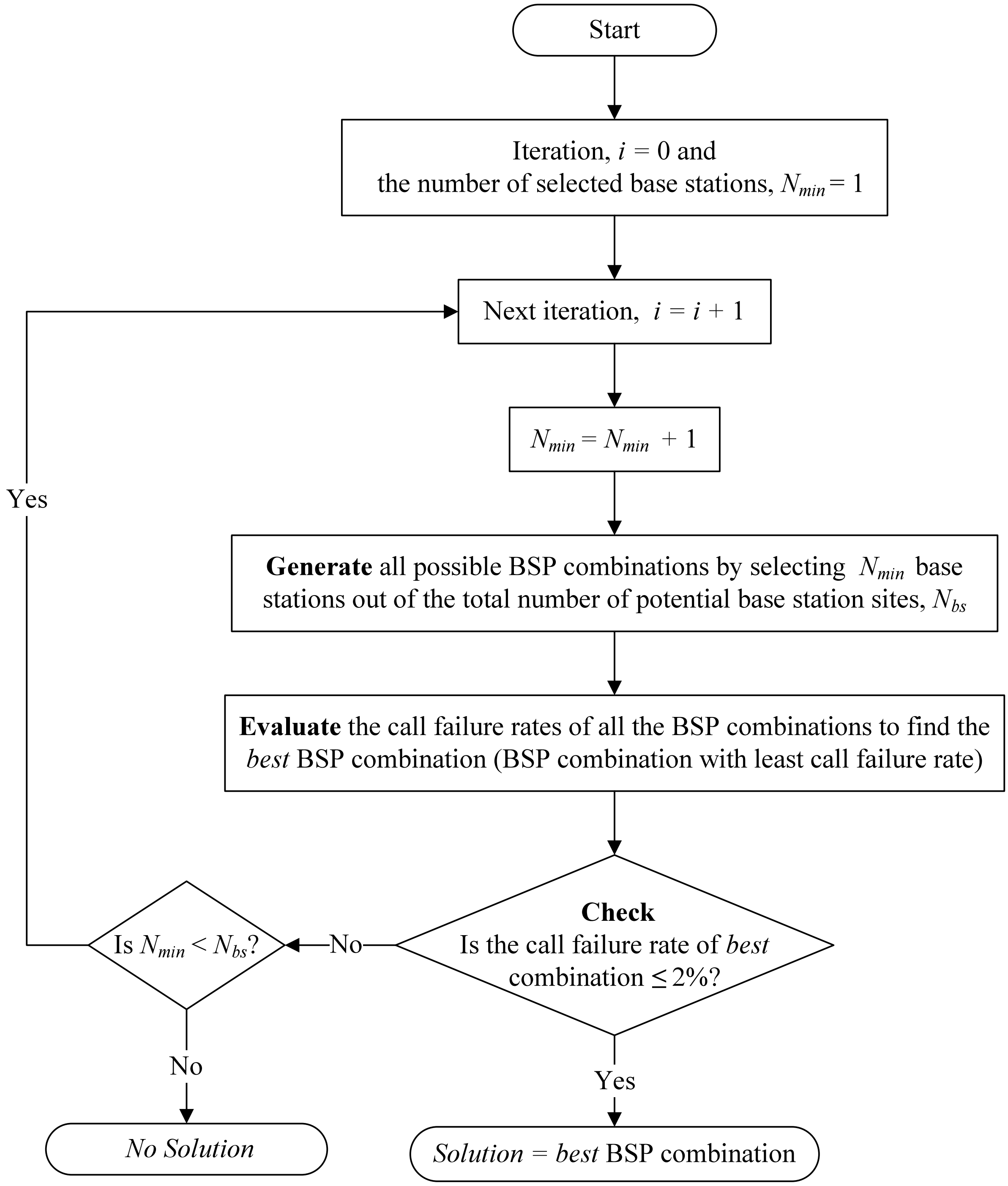


Figure 5.1: Flow diagram for the *BFS* algorithm.

1 1 0 0 1 0 1 0 0 1 0 0

Figure 5.2: An example of a chromosome with 12 bits (potential base station sites) representing a BSP combination with base stations present at sites 1, 2, 5, 7 and 10.

5.2.2 The *Genetic Algorithm* (*GEN*)

The *Genetic Algorithm (GEN)* is a probabilistic algorithm which is implemented by generating an initial population of possible solutions (called chromosomes) that evolves continuously in an attempt to find the optimal solution [60, pp276-279] [67, p141] [78, pp25-28] [79, pp279-283] [80, pp51-141] [81]. When *GEN* is applied to the BSP problem, each chromosome (in a population) represents a BSP combination (i.e. a possible solution) and is made up of N_{bs} bits (or genes) where N_{bs} is the total number of potential base station sites. For example, if there are 12 potential base station sites, a chromosome will be made up of 12 bits. Each bit is either 1 or 0, representing if a base station is present, or not, at a site. Fig. 5.2 shows an example of a chromosome with 12 bits.

In this thesis, a 'standard' implementation of *GEN* is used as implemented by Wong [5, 10] to identify the optimal BSP for indoor systems. The flow diagram for the implementation is shown in Fig. 5.3. First, the algorithm **generates** an initial (first generation) population (of 20 chromosomes) based on the estimate of number of base stations required[6]. Then, it **evaluates** the *cost* of each chromosome in the population (based on the number of base stations selected and the call failure rate) and ranks the chromosomes accordingly. After evaluation, the algorithm **selects** a percentage of the chromosomes in the population (based on their *cost*) as parents[7] to produce the second generation of population. During **reproduction**, the algorithm uses two evolutionary operators, crossover and mutation. Crossover operates on two parent chromosomes when each parent is cut and recombined with a piece of the other to produce two new chromosomes. The crossover point is selected randomly. An example of crossover is shown in Fig. 5.4. The mutation occurs (at a predefined mutation rate) when a bit is turned from 1 to 0 or vice verse as shown in Fig. 5.5.

After reproduction, the second generation of population (of 20 chromosomes) is produced. The algorithm repeats the process of evaluation, selection and reproduction for the second generation to produce the third generation of population. The process of producing new generations of populations is repeated 1000 times and the algorithm finds the *best* chromosome (with the

[6] An estimate of the number of base stations required is provided to select the initial population because a random initial population is unable to find solutions for most BSP problems [5] [82].

[7] The aim is to select chromosomes with low cost from each generation to produce the next generation of population that will (hopefully) have even lower cost.

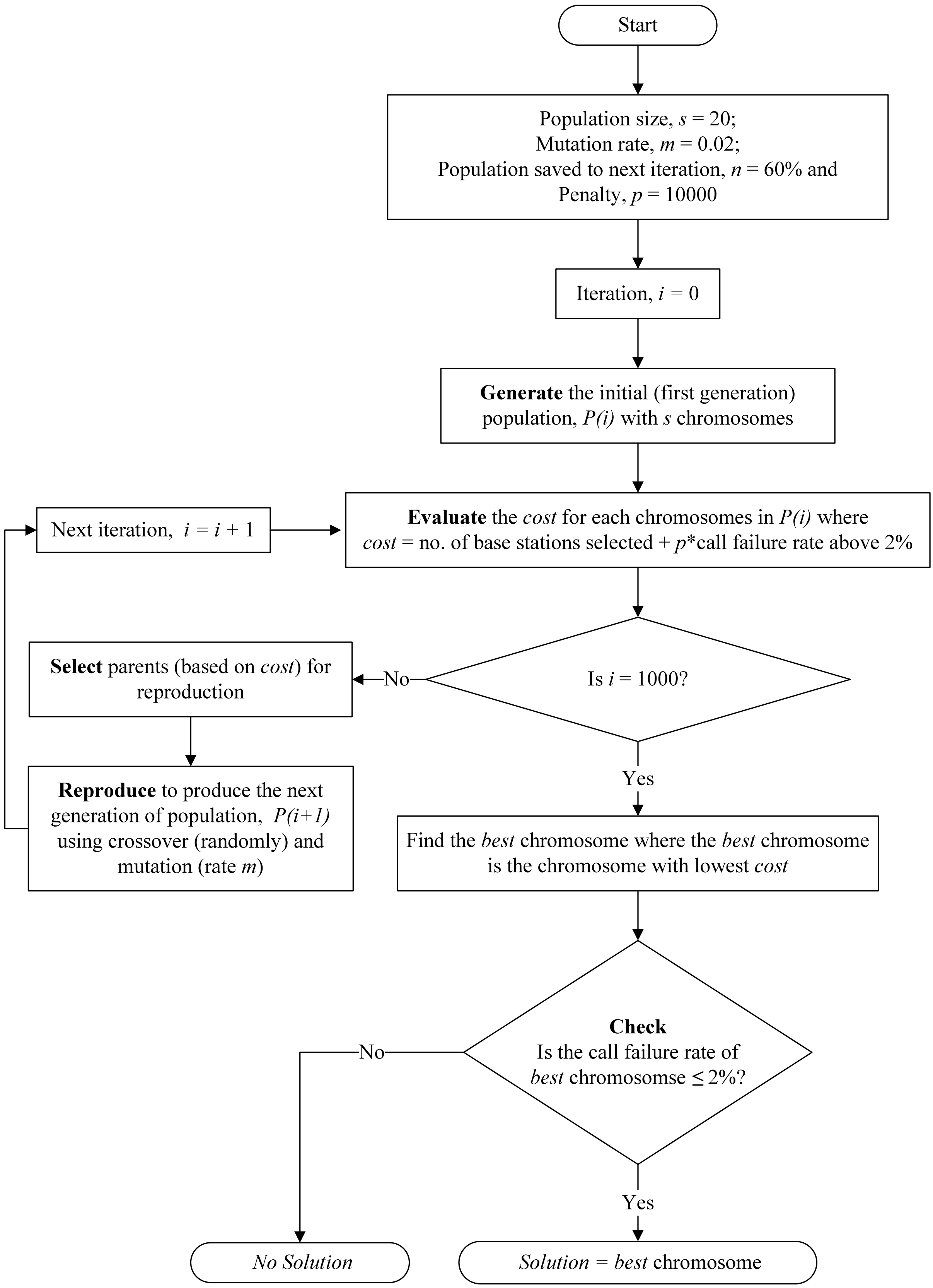


Figure 5.3: Flow diagram for the *GEN* algorithm.

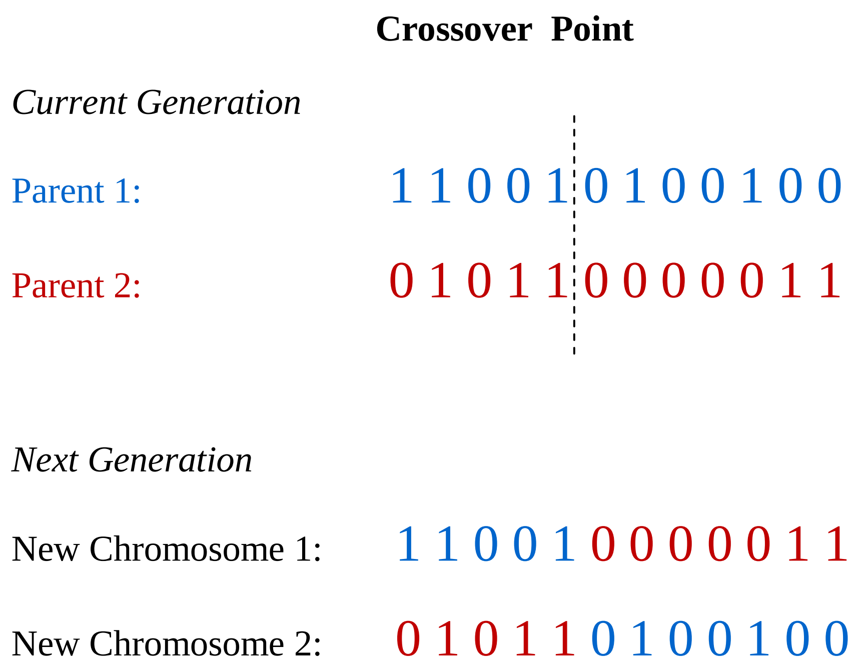


Figure 5.4: An example of crossover between two parents. Each parent is cut and recombined with a piece of the other to produce two new chromosomes.

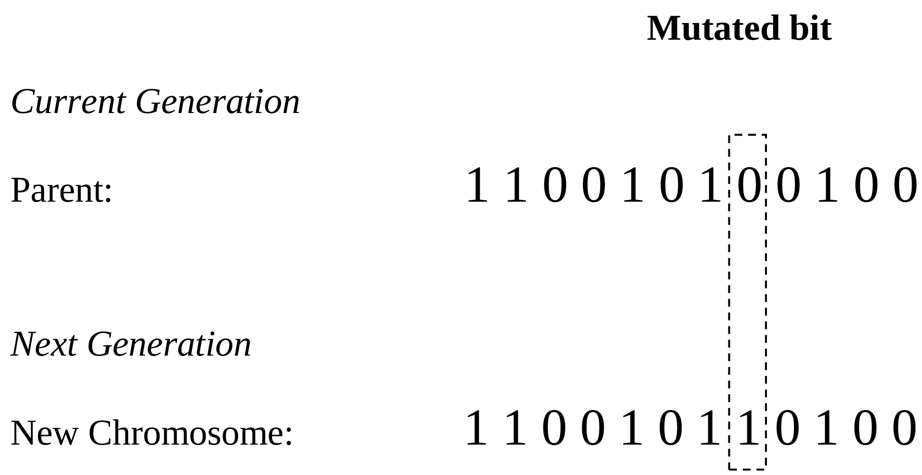


Figure 5.5: An example of mutation where a bit of the parent is turned from 0 to 1 to produce a new chromosome.

lowest *cost*) from all the populations. Then, it **checks** if the *best* chromosome represents an acceptable solution (with call failure rate $\leq 2\%$).

GEN can check a variety of possible solutions without performing exhaustive search but it does not guarantee to find the optimal solution [82]. However, it can provide good approximate solutions for practical problems and has been successfully applied to solve many indoor and outdoor BSP problems [7, 9, 10, 13, 47, 48, 57, 73, 74].

5.2.3 The *Greedy Algorithm* (*GRE*)

The *Greedy Algorithm (GRE)* is a popular heuristic algorithm which is implemented by making the best immediate choice in every iteration with the hope of finding the optimal solution ultimately [66, pp303-304] [83, p145] [84]. The flow diagram for the implementation of *GRE* is shown in Fig. 5.6. The algorithm begins by assuming that there is a base station at each potential base station site in the BSP combination. Then, it **evaluates** the call failure rate of the BSP combination and **checks** if it is an acceptable solution (call failure rate $\leq 2\%$). If it is an acceptable solution, it **removes** the base station connected to the fewest users from the BSP combination. The algorithm is then repeated by evaluating and checking the call failure rate of the BSP combination (with one less potential base station site). If it is an acceptable solution, the base station which serves the fewest users is again removed. The process of removing and reassigning continues until the minimum BSP combination required (to serve the users acceptably) is found.

GRE is generally faster and easier to implement compared to the other algorithms but does not guarantee the optimal solution. However, it can provide approximate solutions and initial estimates and has been implemented for solving the BSP problem in [7, 75, 76]. In this thesis, *GRE* is implemented to examine the *efficiency* (or the speed of execution) of other algorithms.

5.2.4 *Ngadiman's Algorithm* (*NGA*)

Ngadiman [8] proposed a heuristic algorithm (*NGA*) and applied it to find the optimal base station locations for outdoor systems efficiently. *NGA* is implemented by making the best immediate choice in every iteration of a trial[8] and then averaging the results over a large number of trials[9].

In this thesis, the algorithm is applied to the indoor BSP problem. The flow diagram for the implementation of *NGA* is shown in Fig. 5.7. The algorithm applies ***GRE*** to a number of trials separately to find the base stations active for each trial. Then, it **averages** the results of all the

[8] In the context of this thesis, a trial refers to a particular arrangement of users.

[9] The number of users in all the trials is the same but the arrangement (or locations) of users is different.

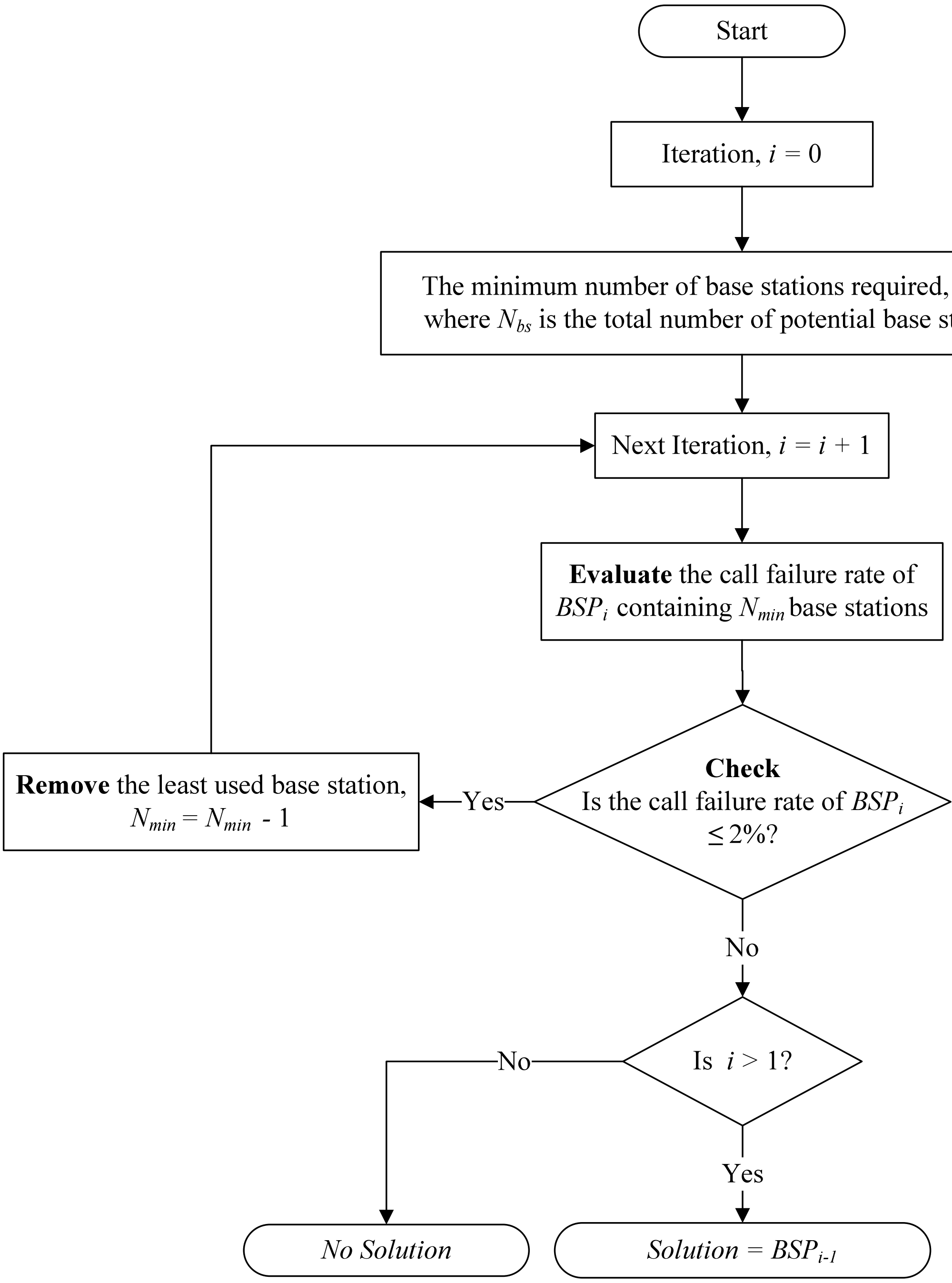


Figure 5.6: Flow diagram for the *GRE* algorithm.

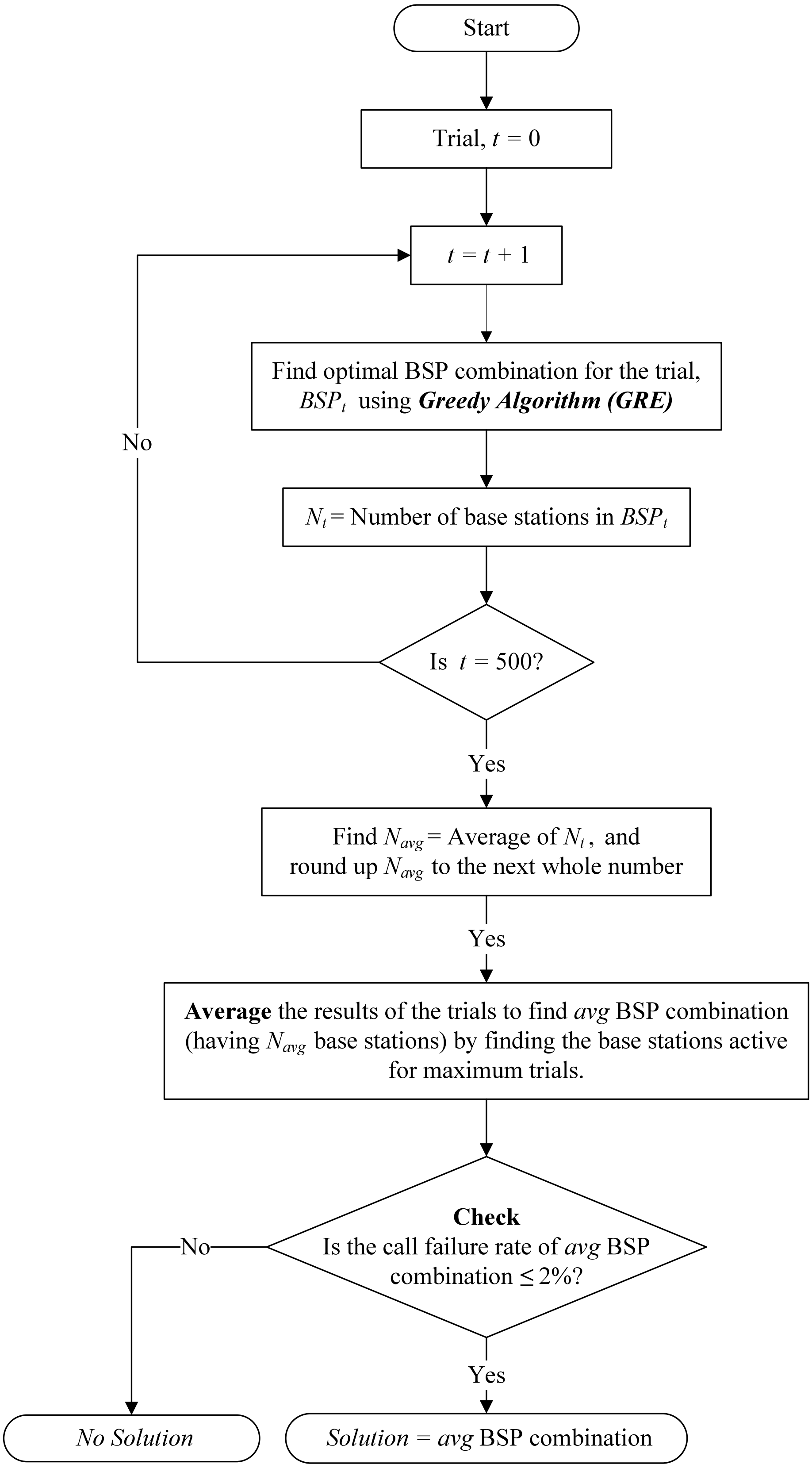


Figure 5.7: Flow diagram for the *NGA* algorithm.

trials to find the *avg* BSP combination and **checks** if the *avg* BSP combination is an acceptable solution (with call failure rate $\leq 2\%$).

Now that the implementations of the four algorithms (*BFS, GEN, GRE* and *NGA*) have been discussed, they can be to applied to an indoor BSP problem to identify which (if any) is the most appropriate algorithm for solving BSP problems.

5.3 Comparison of Existing Algorithms for Base Station Placement

As mentioned in Section 4.2.3, an algorithm is judged by its *accuracy* and *efficiency*. For the BSP problem, the algorithm which selects a smaller number of base stations (satisfying all the constraints) is considered to be more accurate and the algorithm which takes less computational time (to propose a solution) is considered to be more efficient. In this section, the *accuracy* and *efficiency* of the four existing algorithms (*BFS, GEN, GRE* and *NGA*) are compared (for the BSP problem) using a simple case study (Case Study 1).

5.3.1 Physical Environment

The floor layout (with dimensions 20m $\times$ 20m) is shown in Fig. 5.8. The potential base station sites and user locations are indicated by (+) and ($\bigcirc$), respectively. As discussed in Section 4.3.1, a BSP problem is defined using the number of potential base station sites and user locations, path loss estimates, Call Admission Control (CAC) strategy and Grade of Service (GoS).

In Fig. 5.8, there are 20 potential base station sites (i.e. $N_{bs} = 20$) and 120 potential user locations (i.e. $N_u = 120$). Free space propagation is assumed (for simplicity) to find the path loss estimates. The CDMA CAC strategy is used and the values of the CDMA parameters are shown in Table 5.1. The GoS adopted is 2%, i.e. at most 2% of the total calls are lost (or the call failure rate $\leq 2\%$).

5.3.2 Results

Optimisation results are presented for five discrete scenarios[10] (corresponding to 10, 15, 20, 25, and 30 active users). For example, in the first scenario, it is assumed that 10 users are active in each trial. These users are selected (out of the 120 potential user locations) randomly for each

[10]Different scenarios are chosen because they represent a range of possible traffic conditions.

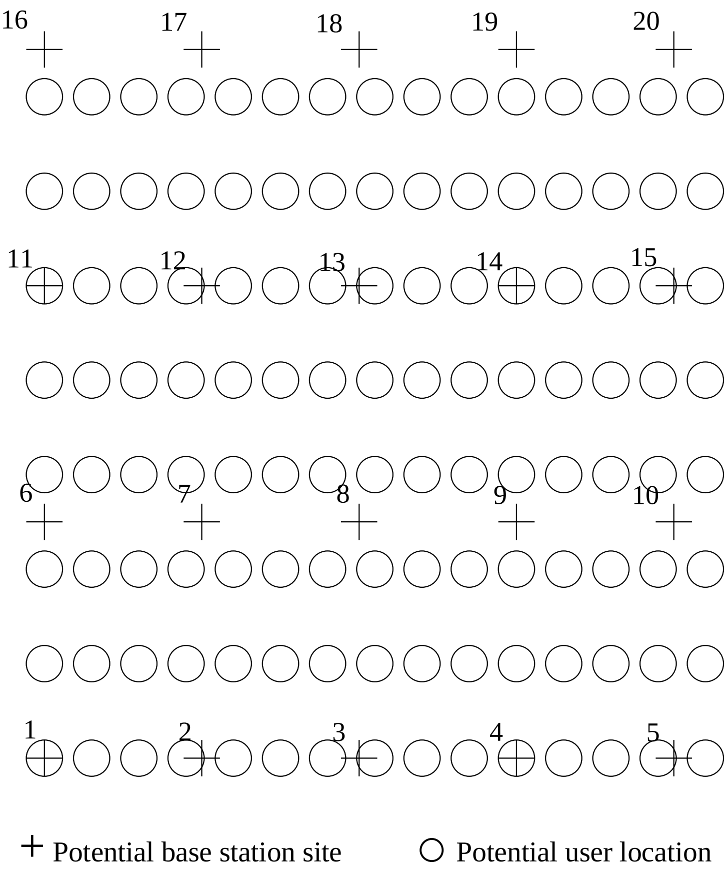


Figure 5.8: Floor layout (20m×20m) for Case Study 1.

trial. All four algorithms (*BFS, GEN, GRE* and *NGA*) are implemented for 500 different trials[11] to find an overall optimal solution rather than finding a solution for one particular trial[12] (or arrangement of users). The *accuracy* and *efficiency* of the algorithms are compared to identify the most appropriate algorithm to solve the indoor BSP problem.

In Fig. 5.9, the *accuracy* of all the algorithms is compared in terms of the number of base stations selected. The figure shows that two base stations are selected by all the algorithms (*BFS, GEN, GRE* and *NGA*) to serve users in the first and second scenarios (10 and 15 active users). Thus, *GEN*, *GRE* and *NGA* are seen to be as accurate as *BFS* in the first and second scenarios. When there are 20 active users, *GEN* is as accurate as *BFS* but *GRE* and *NGA* are not as accurate because they select one extra base station. The results show that none of the three algorithms (*GEN, GRE* and *NGA*) are as accurate as *BFS* when there are 25 and 30 active users.

[11] The results are presented for 500 trials because an extensive program of trials for 100, 500, 1000 and 100,000 trials demonstrated that 500 trials can represent the system with a call failure rate accurate to one decimal place compared to 100,000 trials.

[12] *BFS, GEN* and *GRE* are implemented on all the trials together but *NGA* is applied to each trial separately and the results are averaged to find the optimal BSP.

CDMA Parameter	Value
Operating frequency (f)	1.8GHz
Processing gain (G_p)	128
Forward link SIR threshold (Q_f)	8.45dB
Reverse link SIR threshold (Q_r)	7dB
Transmission power of base station (per user) (P_{t1})	1mW
Received power at base station (per user) (P_{tar})	1nW
Maximum transmission power of user (P_{max})	1mW
Minimum received power at user (P_{min})	1pW

Table 5.1: Values of the CDMA parameters used for Case Study 1.

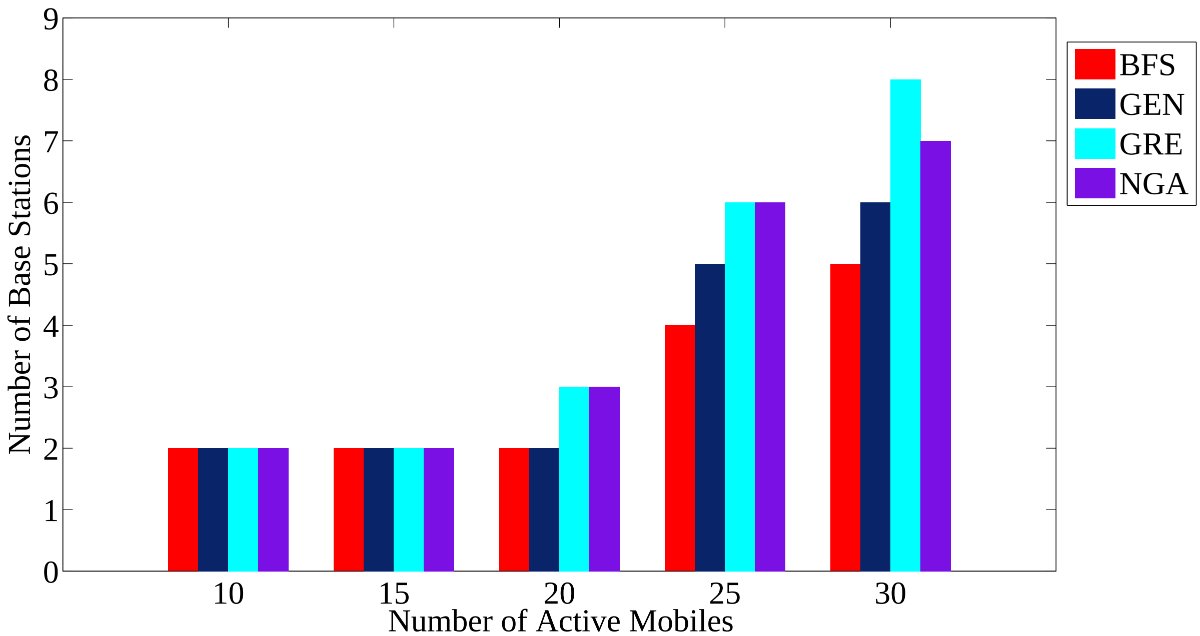


Figure 5.9: Comparison of *accuracy* of the algorithms for the five scenarios of Case Study 1. *Accuracy* is measured in terms of the number of base stations selected i.e. the algorithm which selects smaller number of base stations is considered to be more accurate.

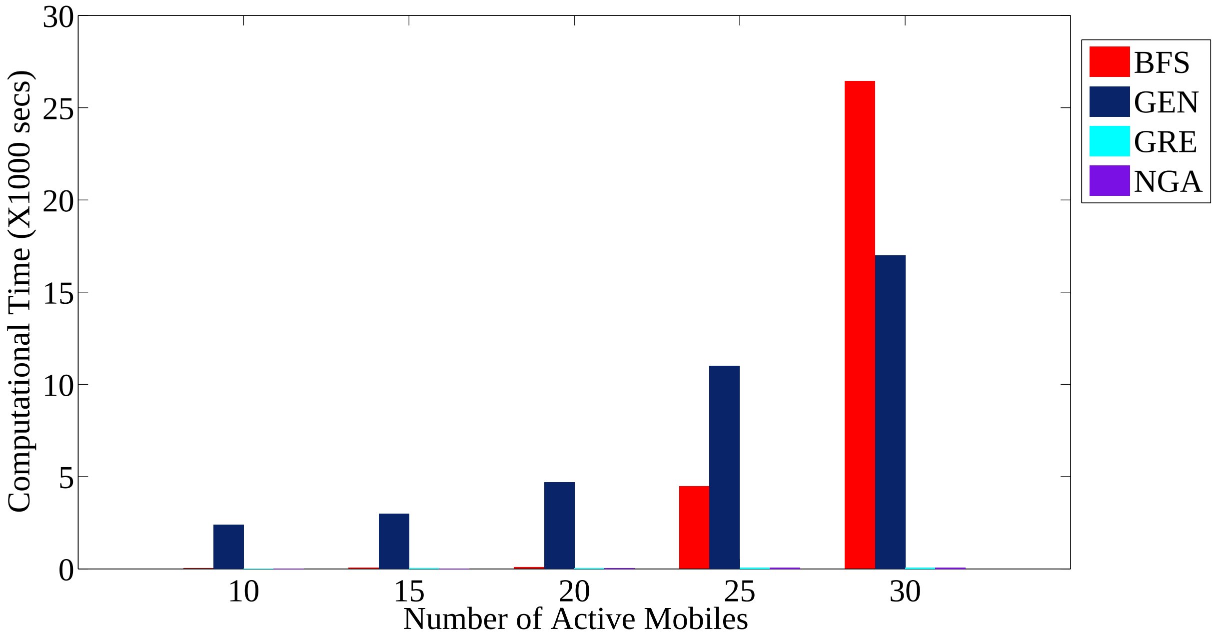


Figure 5.10: Comparison of *efficiency* of the algorithms for the five scenarios of Case Study 1. *Efficiency* is measured in terms of the computational time i.e. the algorithm which has a lower computational time is considered to be more efficient.

In Fig. 5.10, the *efficiency* of all the algorithms is compared in terms of computational time. The figure shows the time taken by all the algorithms (except *GEN*) for 10, 15 and 20 active users is similar and very short. The computational time for *GEN* is higher (than *BFS*, *GRE* and *NGA)* for the first four scenarios (10, 15, 20 and 25 active users). Thus, *BFS*, *GRE* and *NGA* are more efficient than *GEN* for the first four scenarios. When there are 30 active users, the computational time is lowest for *GRE* and *NGA*, and highest for *BFS*. Thus, *BFS* is the least efficient algorithm for 30 active users.

Figs. 5.9 and 5.10 have been combined in Fig. 5.11 so that the *accuracy* and *efficiency* of the algorithms can be compared simultaneously. Fig. 5.11 shows the number of base stations selected and the computational time (in kiloseconds, ks) for all the scenarios (i.e. 10, 15, 20, 25, and 30 active users). For example, when there are 30 active users, *BFS* selects five base stations whereas *GEN* selects six, *NGA* selects seven and *GRE* selects eight base stations. Thus, *BFS* is the most accurate and *GRE* is the least accurate algorithm for 30 active users. The computational time (i.e. stick height) is observed to be lowest for *GRE* and *NGA* and highest for *BFS* when there are 30 active users. Thus, *GRE* and *NGA* are the most efficient and *BFS* is the least efficient algorithm for 30 active users. Ideally, an algorithm should select the least number of base stations (i.e. equal to the number of base stations selected by *BFS* (red sticks)), and have the shortest computational time (i.e. shortest stick height).

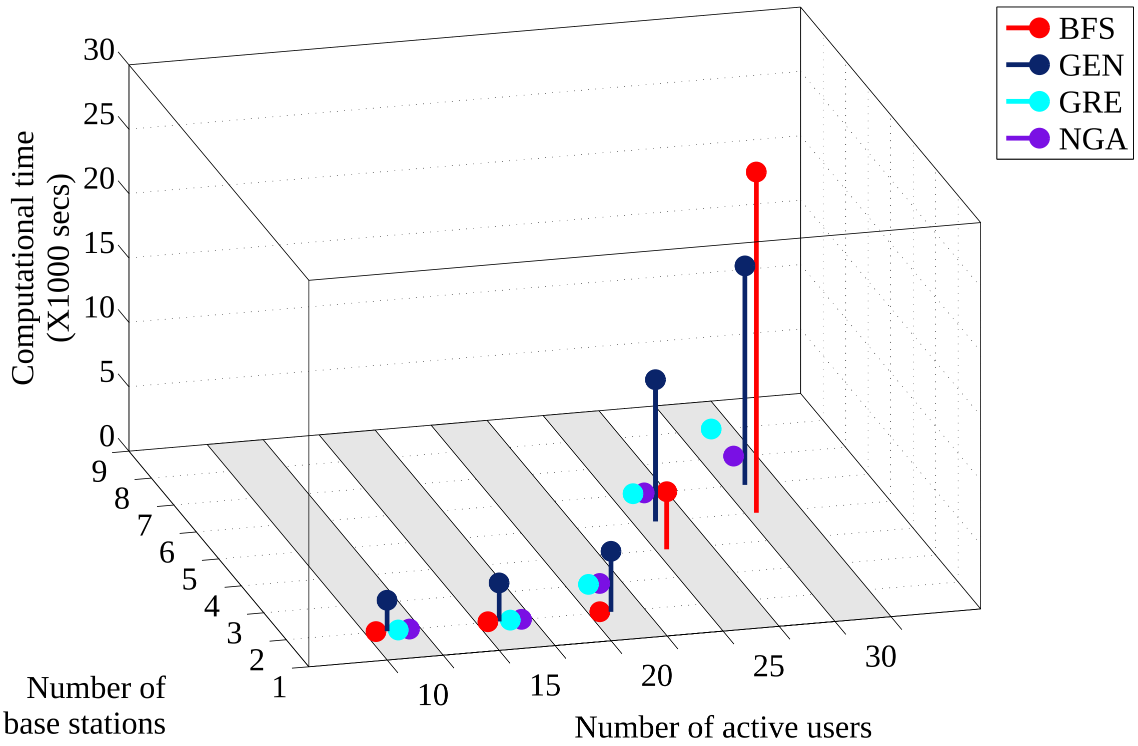


Figure 5.11: Comparison of *accuracy* (number of base stations selected) and *efficiency* (computational time) of the algorithms for the five scenarios (grey bars) of Case Study 1. All sticks in a given grey bar are the results (obtained by the four algorithms) for a particular scenario. The sticks are spatially separated to clearly show the results (i.e. without overlap). Ideally, an algorithm should select the least number of base stations (i.e. equal to the number of base stations selected by *BFS* (red sticks)), and have the shortest computational time (i.e. shortest stick height).

5.3.3 Discussion

The results indicate that the *BFS* algorithm identifies the optimal solution for all the scenarios as it performs an exhaustive search. However, the computational time for *BFS* increases markedly as the number of active users increases, making it unsuitable for problems other than those that are very simple.

GEN algorithm identifies optimal results for a small number of active users (10, 15 and 20 active users) but it selects an extra base station for 25 and 30 active users. Thus, in this case study, the accuracy of *GEN* decreases as the number of active users increases. However, *GEN* is more accurate than *NGA* and *GRE*. The computational time for *GEN* is higher than other algorithms for most of the scenarios considered. Nevertheless, *GEN* is more efficient than *BFS* for large problems. A more sophisticated customisation of *GEN* may improve its accuracy but with potentially greater computational time [5].

The *NGA* and *GRE* algorithm select extra base stations in three (out of five) scenarios. Thus, both the algorithms are less accurate compared to the other algorithms but are substantially more efficient. Therefore, *NGA* and *GRE* can be useful if efficiency is more important than accuracy but that is not true for most practical applications as adding extra base stations increases deployment costs.

Fig. 5.12 summarises the results for Case Study 1 and shows the relative *accuracy* and *efficiency* of the four existing algorithms. The results indicate that the existing algorithms considered in this chapter are seen to provide an almost mutually exclusive tradeoff between *accuracy* and *efficiency*. *BFS* and *GEN* are observed to be accurate but not very efficient whereas *GRE* and *NGA* are efficient but not accurate. Ideally, the aim is to find an algorithm which can combine the advantages of the existing algorithms and negate the disadvantages i.e. give an optimal solution (like *BFS* and *GEN*) and have short computational time (like *GRE* and *NGA*). Thus, in Chapter 6, a new hybrid algorithm has been developed to achieve the desired aim.

5.4 Summary

In this chapter, four existing algorithms (Brute Force Search (*BFS*), Genetic Algorithm (*GEN*), Greedy Algorithm (*GRE*) and Ngadiman's Algorithm (*NGA*)) for solving the Base Station Placement (BSP) problem have been implemented and compared using a case study. The performances of the four algorithms are compared in terms of accuracy (i.e. number of base stations selected to serve the users while satisfying all the constraints) and efficiency (i.e. computational time).

BFS selects the least number of base stations for all the scenarios but is limited to solving small-sized problems because its computational time increases markedly as the number of ac-

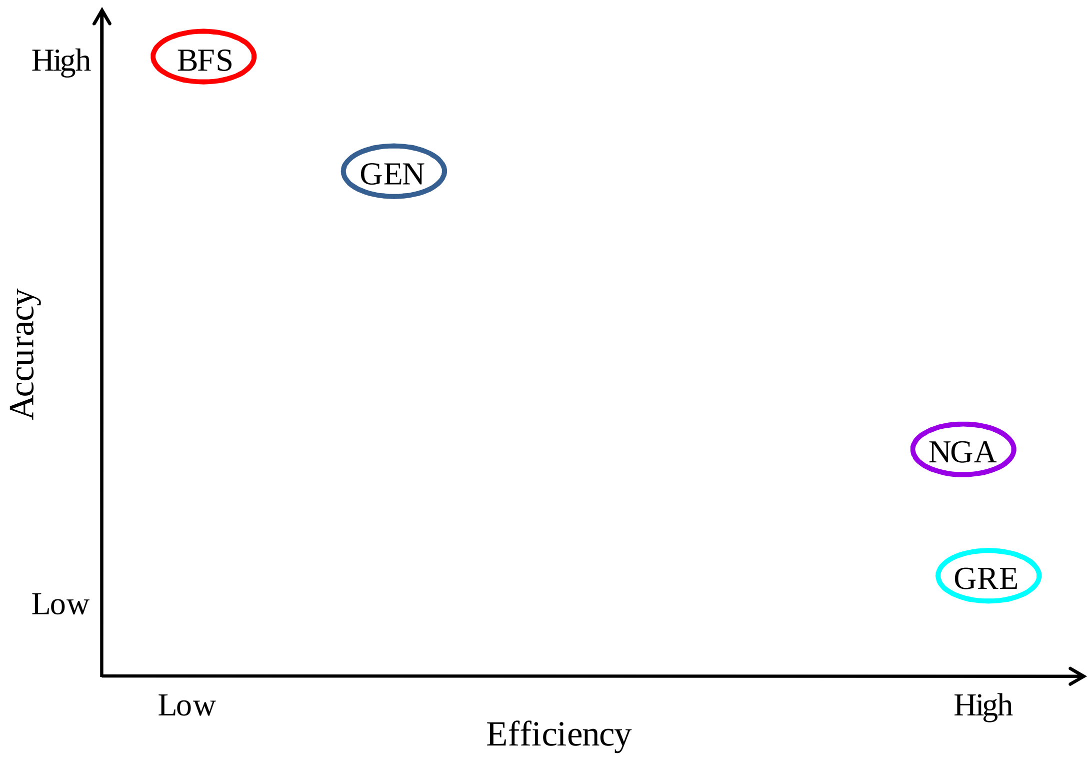


Figure 5.12: Relative *accuracy* and *efficiency* of the four algorithms.

tive users increases. The results indicate that *GEN* becomes less accurate as the number of active users increases and has high computational time. *NGA* and *GRE* are the most efficient algorithms (having least computational time) but arrive at less accurate results (with extra base stations) which would increase the deployment costs. Thus, the existing algorithms are seen to provide an almost mutually exclusive tradeoff between accuracy and efficiency. In Chapter 6, a new hybrid algorithm has been proposed which aims to combine the advantages of the existing algorithms and negate the disadvantages.

Chapter 6

Development of a Hybrid Algorithm — *RCR*

6.1 Introduction

In Chapter 5, the third stage of optimisation[1] was applied to identify an appropriate algorithm to solve the indoor Base Station Placement (BSP) problem. Four existing[2] algorithms relevant to solving the indoor BSP problem (Brute Force Search (*BFS*), Genetic Algorithm (*GEN*), Greedy Algorithm (*GRE*) and Ngadiman's Algorithm (*NGA*)) were identified and compared using a case study. The results indicated that these algorithms provided an almost mutually exclusive tradeoff between *accuracy* and *efficiency*. In particular, *BFS* and *GEN* were observed to be accurate but not very efficient whereas *GRE* and *NGA* were efficient but not accurate.

The aim of this chapter is to propose an algorithm which can combine the advantages of the existing algorithms i.e. have high *accuracy* (like *BFS* and *GEN*) and high *efficiency* (like *GRE* and *NGA*). Therefore, a new hybrid algorithm, ***RCR***[3] has been developed and is described in Section 6.2. In Section 6.3, this new algorithm is compared to the four existing algorithms (*BFS, GEN, GRE* and *NGA*) to identify which (if any) is the most appropriate algorithm for solving the indoor BSP problem. The chapter is summarised in Section 6.4.

6.2 The Hybrid Algorithm

In Section 5.3, four existing algorithms (Brute Force Search (*BFS*), Genetic Algorithm (*GEN*), Greedy Algorithm (*GRE*) and Ngadiman's Algorithm (*NGA*)) for solving the indoor Base Sta-

[1]The stages of optimisation were discussed in Chapter 4 (Fig. 4.1).

[2]The existing algorithms are the algorithms which have been proposed in the past to solve the BSP problem.

[3]***RCR*** stands for ***R****eduction Estimation* followed by ***C****ombinatorial Optimisation* either alone or in conjunction with ***R****eduction Approximation.*

tion Placement (BSP) problem were compared in terms of *accuracy* (number of base stations selected) and *efficiency* (computational time). *BFS* selected the least number of base stations but its computational time increased markedly as the number of active users increased. *GEN* became inaccurate (i.e. selected extra base stations) as the number of active users increased and had high computational time. *NGA* and *GRE* were the most efficient algorithms (i.e. had least computational time) but arrived at inaccurate results. Thus, the results (summarised in Fig. 5.12) indicated that the existing algorithms (considered) provide an almost mutually exclusive tradeoff between *accuracy* and *efficiency*.

In this section, the aim is to propose an algorithm which can combine the advantages of the existing algorithms and negate the disadvantages. A new hybrid algorithm — termed ***RCR*** — has been developed as a possible solution, and is divided into two stages:

I. ***R****eduction Estimation;* and

II. ***C****ombinatorial Optimisation* with or without ***R****eduction Approximation* depending on the size of the system.

Stage I of *RCR* estimates the minimum number of base stations required and Stage II finds the optimal BSP combination to serve the users. During the implementation of the existing algorithms, it was observed that customising *GEN,* by giving an estimate of the number of base stations, improved its performance significantly. Thus, a good initial estimate may improve the accuracy of an algorithm [5,82]. However, it is important that the algorithm used for estimation has short computational time (like *GRE*). Therefore, Stage I of *RCR*, *Reduction Estimation* estimates the minimum number of base stations required using *GRE*. This reduces the solution space and it is then possible to use *Combinatorial Optimisation* (selective *BFS*) either alone or in conjunction with *Reduction Approximation* (modified *NGA*) in Stage II to find the optimal solution. The stages of *RCR* are shown in the flow diagram in Fig. 6.1.

Stage I — *Reduction Estimation*

In the first stage of *RCR*, the aim is to estimate the minimum number of base stations required to serve a given set of users. The implementation of *Reduction Estimation* is similar to *GRE*.

Reduction Estimation begins by assuming that there is a base station at each potential base station site in the BSP combination. Then, it evaluates the call failure rate of the BSP combination and checks if it is $\leq 4\%$ (twice the final target of 2%)[4]. If the call failure rate is $\leq 4\%$, it removes the base station connected to the fewest users from the BSP combination. The algorithm is then repeated by evaluating and checking the call failure rate of the BSP combination

[4] In this stage, the aim is to only estimate the minimum number of base stations required to serve the users rather than finding the optimal BSP combination. Therefore, the Grade of Service (GoS) criteria is relaxed to 4% (twice the final target of 2%). The value of 4% is selected empirically and values other than 4% will still yield a solution but at the cost of greater computation in Stage II.

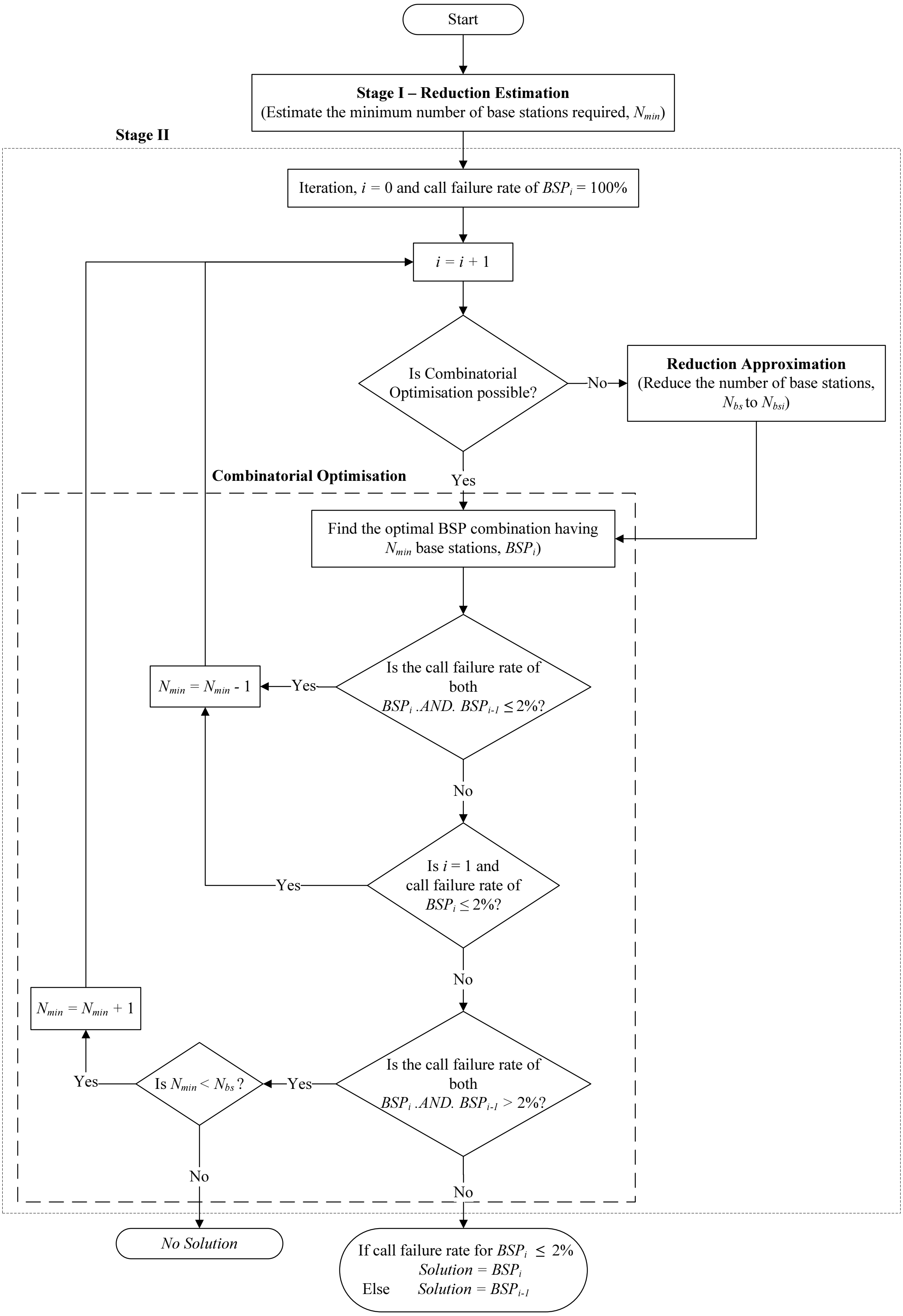


Figure 6.1: Flowchart for the *RCR* Algorithm.

(with one less potential base station site). The process of removing and reassigning continues until the minimum BSP combination required to serve with a call failure rate $\leq 4\%$ is found. The number of base stations in the BSP combination is the estimate of the minimum number of base stations required, N_{min}. The optimal BSP combination (to serve the users with a call failure rate of $\leq 2\%$) is found in the second stage of the *RCR* algorithm using either *Combinatorial Optimisation* directly or after *Reduction Approximation*.

Stage II — *Combinatorial Optimisation (directly) or (after) Reduction Approximation*

In the second stage, the aim is to find the BSP combination with the minimum number of base stations which can serve the users with a call failure rate $\leq 2\%$. The estimate of the minimum number of base stations required (N_{min}) out of the total number of potential base station sites (N_{bs}) is found using *Reduction Estimation* (Stage I). The total number of possible combinations of base stations for *Combinatorial Optimisation* is ${}^{N_{bs}}C_{N_{min}}$. As the value of N_{bs} or N_{min} increases, the computational time becomes very large [7] [62, p17] [66, p118]. Thus, *Combinatorial Optimisation* is used if the computation is feasible within a few hours[5] (as might be encountered in a small-medium sized indoor system), otherwise (for large indoor systems) *Reduction Approximation* is first used to reduce the number of base stations considered so that *Combinatorial Optimisation* can be used.

Combinatorial Optimisation

The algorithm generates all possible BSP combinations[6] containing N_{min} base stations. Then, it evaluates the call failure rate of the generated combinations and checks if the call failure rate of any BSP combination is $\leq 2\%$. If a BSP combination with a call failure rate $\leq 2\%$ is found, the value of N_{min} is decremented by one and the process of generation, evaluation and checking is repeated. This process continues until N_{min} is too small to yield an acceptable solution (with call failure rate $\leq 2\%$) .

If the call failure rate of all the BSP combinations generated from the initial estimate is $> 2\%$, N_{min} is incremented by one and the the process of generation, evaluation and checking is repeated[7]. This process continues until it is possible to find an acceptable solution using *Combinatorial Optimisation*. The BSP combination with the minimum number of base stations

[5]In this thesis, *Combinatorial Optimisation* is performed when the number of combinations is ≤ 2000.

[6]The total number of possible combinations of base stations is ${}^{N_{bs}}C_{N_{min}}$.

[7]In almost all the case studies considered in this research, the search did not need to be repeated more than once because the *Reduction Estimation* stage was sufficiently accurate.

(and call failure rate of $\leq 2\%$) is considered to be optimal. *Reduction Approximation* is used first if it is not practical to perform *Combinatorial Optimisation* directly.

Reduction Approximation

Reduction Approximation is used to reduce the computational time of the *Combinatorial Optimisation* stage by reducing the number of combinations. The value of N_{bs} needs to be reduced because N_{min} (found by *Reduction Estimation* in Stage I) is fixed. *Reduction Approximation* (in Stage II) is similar to *NGA* in its implementation. The solution obtained is used to remove the least used base station sites so that N_{bs} reduces.

For each trial, *Reduction Approximation* begins by assuming that there is a base station at each potential base station site in the BSP combination. Then, the algorithm evaluates the call failure rate of the BSP combination and checks if this rate is $\leq 2\%$. If the call failure rate is $\leq 2\%$, it removes the base station connected to the fewest users from the BSP combination. The algorithm is then repeated by evaluating and checking the call failure rate of the BSP combination (with one less potential base station site). The process of removing and reassigning continues until the minimum BSP combination required to serve with a call failure rate $\leq 2\%$ is found. This process is repeated for several trials to find the base station sites active for each trial. The number of possible base station sites, N_{bs} is reduced by removing the sites which are active for least trials so that the number of combinations is reduced and *Combinatorial Optimisation* can be performed to obtain the optimal BSP combination.

Thus, *RCR* is a hybrid algorithm which is implemented in two stages and uses the existing algorithms to combine their advantages. Now that the implementation of *RCR* has been discussed, it can be compared (in terms of *accuracy* and *efficiency)* to the four existing algorithms (*BFS, GEN, GRE* and *NGA*) implemented in Chapter 5.

6.3 Comparison of Hybrid and Existing Algorithms for Base Station Placement

An algorithm is judged by its *accuracy* and *efficiency* [66, p3]. In this section, the *accuracy* and *efficiency* of the hybrid algorithm *(RCR)* and the four existing algorithms (*BFS, GEN, GRE* and *NGA*) are compared. In Chapter 5, the four existing algorithms (*BFS, GEN, GRE* and *NGA*) were implemented and compared using a case study (Case Study 1). It is appropriate to apply *RCR* to the same case study[8] for comparative purposes.

[8] The five algorithms will be applied to more case studies in Chapter 7 for extensive comparison.

6.3.1 Physical Environment

As the case study from Section 5.3 (i.e. Case Study 1) is used, the floor layout is identical to that in Section 5.3.1 (shown in Fig. 5.8). The problem definition (i.e. the number of potential base station sites and user locations, path loss estimates, Call Admission Control (CAC) strategy and Grade of Service (GoS)) is also identical to that in Section 5.3.1. Thus, there are 20 potential base station sites (i.e. $N_{bs} = 20$), 120 potential user locations (i.e. $N_u = 120$) and free space propagation is assumed to find the path loss estimates. The CDMA Call Admission Control (CAC) strategy is used and the values of the CDMA parameters are shown in Table 5.1. The Grade of Service (GoS) adopted is 2%, i.e. at most 2% of the total calls are lost (or the call failure rate $\leq 2\%$).

6.3.2 Results

The optimisation results presented in this section are for the same five scenarios (corresponding to 10, 15, 20, 25, and 30 active users) as presented in Section 5.3.2[9]. *RCR* is also implemented for 500 different trials[10] to find an overall optimal solution rather than finding a solution for one particular trial. In this section, *accuracy* and *efficiency* of the five algorithms (*BFS, GEN, GRE, NGA* and *RCR*) are compared to identify the most appropriate algorithm to solve the indoor BSP problem.

In Fig. 6.2, the *accuracy* of all the algorithms is compared in terms of the number of base stations selected. The figure shows that two base stations are selected by all the algorithms (*BFS, GEN, GRE, NGA* and *RCR*) to serve users in the first and second scenarios (10 and 15 active users). Thus, *GEN*, *GRE, NGA* and *RCR* are seen to be as accurate as *BFS* in the first and second scenarios. When there are 20 active users, *GEN* and *RCR* are as accurate as *BFS* but *GRE* and *NGA* are not as accurate as they select one extra base station. The results show that only *RCR* is as accurate as *BFS* when there are 25 and 30 active users.

In Fig. 6.3, the *efficiency* of all the algorithms is compared in terms of computational time. The figure shows the time taken by all the algorithms (except *GEN*) for 10, 15 and 20 active users is similar and very short. When there are 25 active users, the computational time of *RCR* is higher than *GRE* and *NGA* but lower than *BFS* and *GEN*. Thus, *RCR* is less efficient than *GRE* and *NGA* but more efficient than *BFS* and *GEN* for 25 active users.

Figs. 6.2 and 6.3 have been combined in Fig. 6.4 so that the *accuracy* and *efficiency* of the algorithms can be compared simultaneously. Fig. 6.4 shows the number of base stations selected and the computational time (in kiloseconds, ks) for all the scenarios. For example, when there

[9] In Section 5.3.2, results were presented to compare the four existing algorithms (*BFS, GEN, GRE* and *NGA*).

[10] In Section 5.3.2, the four existing algorithms (*BFS, GEN, GRE* and *NGA*) were implemented for 500 different trials.

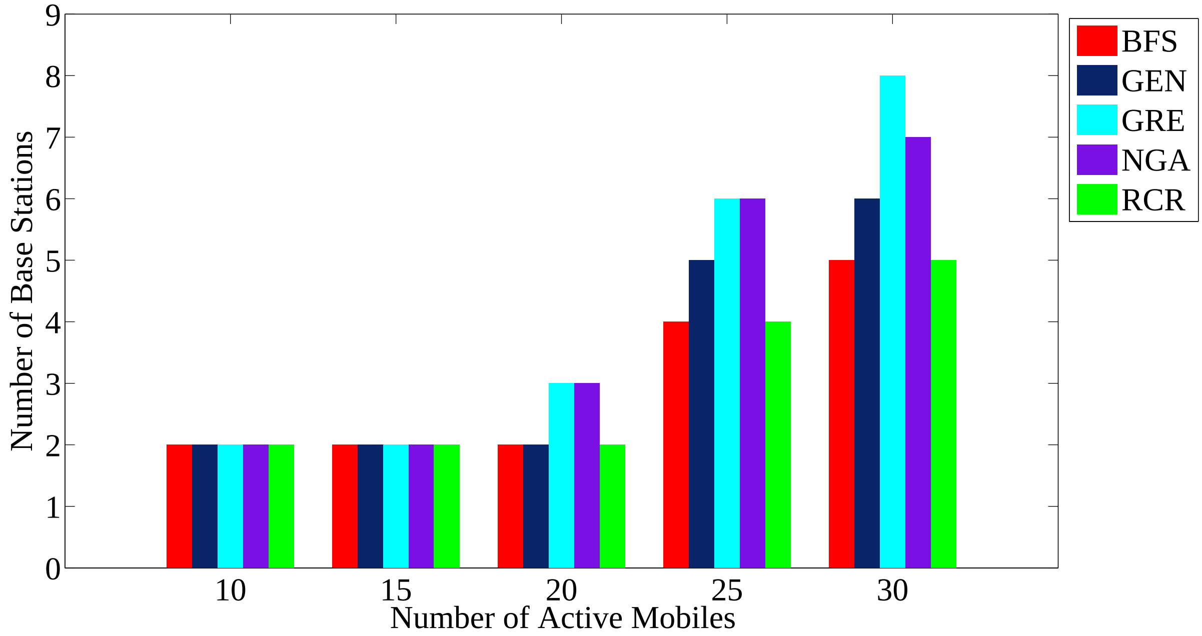


Figure 6.2: Comparison of *accuracy* of the algorithms for the five scenarios of Case Study 1. *Accuracy* is measured in terms of the number of base stations selected i.e. the algorithm which selects smaller number of base stations is considered to be more accurate.

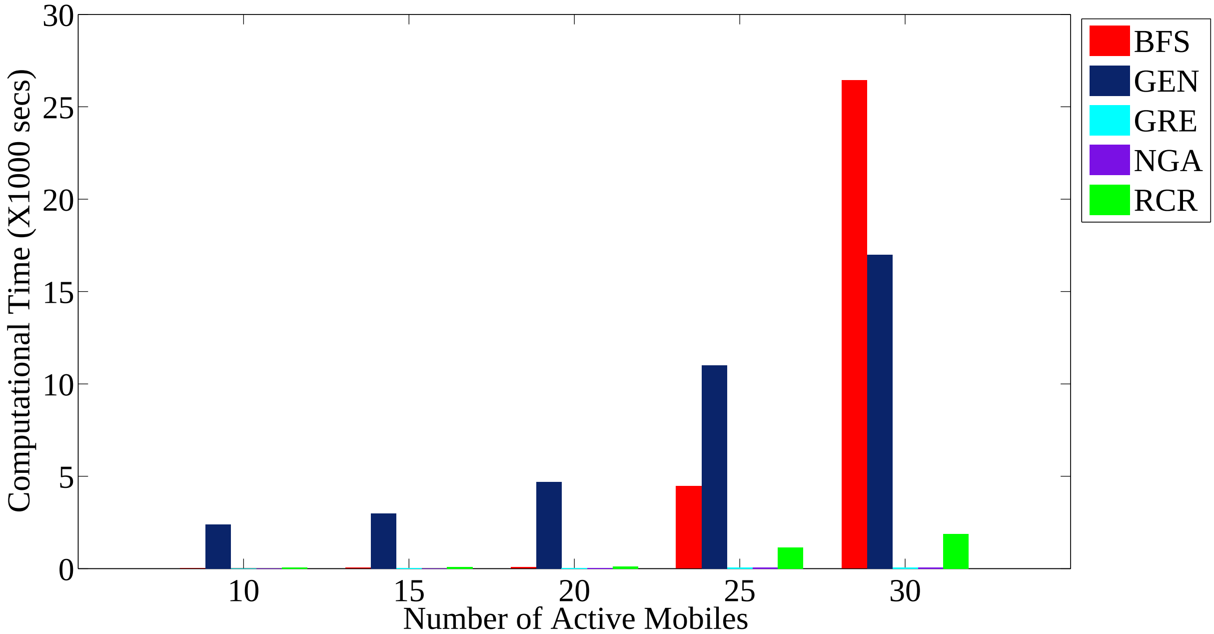


Figure 6.3: Comparison of *efficiency* of the algorithms for the five scenarios of Case Study 1. *Efficiency* is measured in terms of the computational time i.e. the algorithm which has a lower computational time is considered to be more efficient.

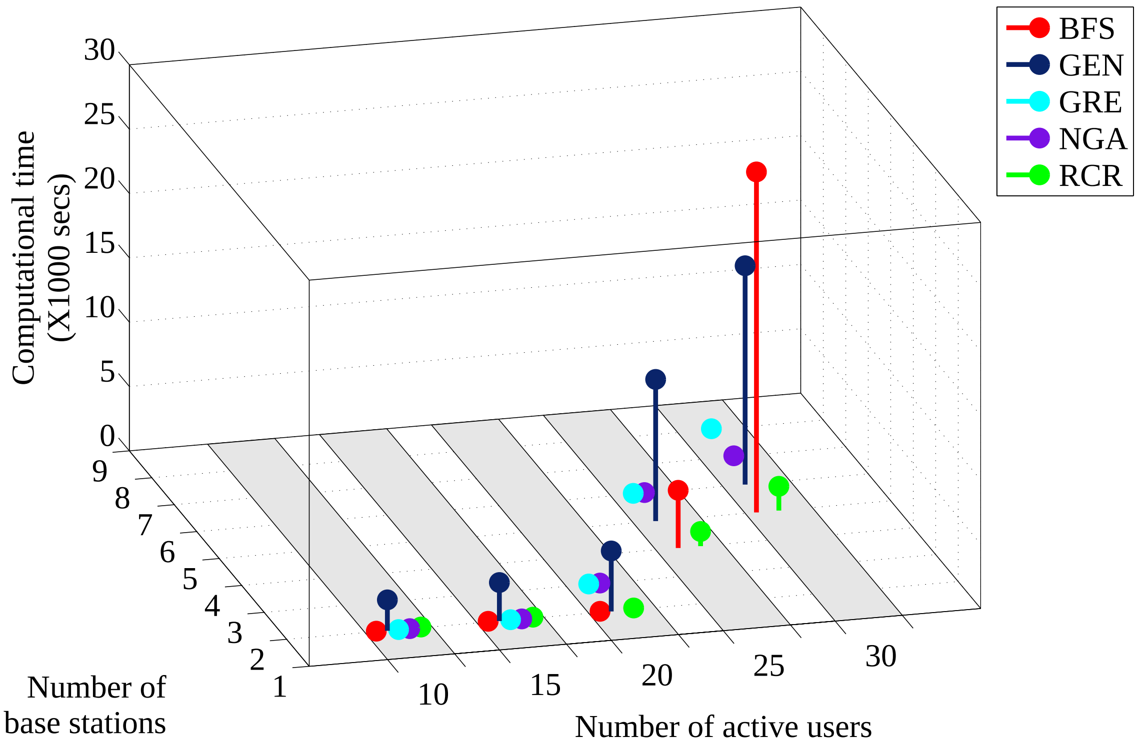


Figure 6.4: Comparison of *accuracy* (number of base stations selected) and *efficiency* (computational time) of the algorithms for the five scenarios (grey bars) of Case Study 1. All sticks in a given grey bar are the results (obtained by the five algorithms) for a particular scenario. The sticks are spatially separated to clearly show the results (i.e. without overlap). Ideally, an algorithm should select the least number of base stations (i.e. equal to the number of base stations selected by *BFS* (red sticks)), and have the shortest computational time (i.e. shortest stick height).

are 30 active users, *BFS* and *RCR* select five base stations whereas *GEN* selects six, *NGA* selects seven and *GRE* selects eight base stations. Thus, *BFS* and *RCR* are the most accurate algorithms and *GRE* is the least accurate algorithm for 30 active users. The computational time of *RCR* is observed to be lower than *BFS* and *GEN* and higher than *GRE* and *NGA* when there are 30 active users. Thus, *RCR* is less efficient than *GRE* and *NGA* but more efficient than *BFS* and *GEN* when there are 30 active users.

6.3.3 Discussion

As discussed in Section 5.3.3, *BFS* algorithm identifies the optimal solution for all the scenarios as it performs exhaustive search. However, the computational time for *BFS* increases markedly as the number of active users increases, making it unsuitable for problems other than those that are very simple. Accurate results are obtained from the *GEN* algorithm for a small number of active users but its accuracy decreases as the number of active users increases. However, *GEN* is more efficient than *BFS* for large problems. Both *NGA* and *GRE* are less accurate compared to the other algorithms but are substantially more efficient.

It is observed that the *RCR* algorithm selects the same number of base stations as *BFS* for all the scenarios and is more accurate than *GEN*, *NGA* and *GRE*. The computational time of *RCR* is lower than *BFS* and *GEN* but higher than *NGA* and *GRE*. However, the computational time of *RCR* remains feasible for practical applications.

Fig. 6.5 summarises the results for Case Study 1 and shows the relative *accuracy* and *efficiency* of the four existing algorithms and the hybrid algorithm. The existing algorithms (*BFS, GEN, GRE* and *NGA*) are seen to provide an almost mutually exclusive tradeoff between *accuracy* and *efficiency*. However, the hybrid algorithm, *RCR* in this albeit limit trial, is seen to provide superior results without sacrificing *accuracy* and *efficiency*.

The results presented in this section are based on one case study (Case Study 1) which considers free space propagation. Case Study 1 discussed herein was contrived for ease of implementation and to permit an initial assessment of performance. In Chapter 7, two more case studies (Case Studies 2 and 3), based on the path loss values found by in-building experimental measurements, are presented to compare the five algorithms in different environments.

6.4 Summary

In this chapter, a new hybrid algorithm (***RCR***) has been proposed for solving the Base Station Placement (BSP) problem for indoor wireless communication systems. In this algorithm, ***R****eduction Estimation* estimates the minimum number of base stations required to serve a given

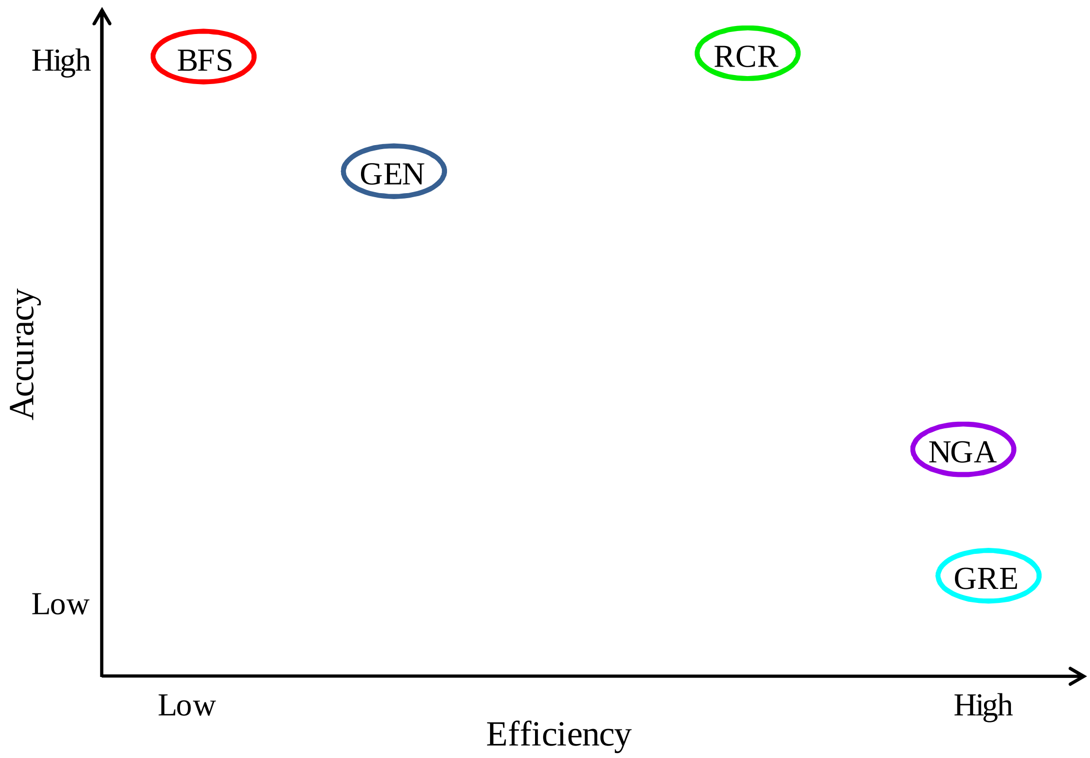


Figure 6.5: Relative *accuracy* and *efficiency* of the five algorithms.

set of users, and ***C**ombinatorial **O**ptimisation* (either alone or in conjunction with ***R**eduction Approximation*) identifies the optimal BSP combination for the given set of users.

RCR is compared to the four existing algorithms[11] (Brute Force Search (*BFS*), Genetic Algorithm (*GEN*), Greedy Algorithm (*GRE*) and Ngadiman's Algorithm (*NGA*)) in terms of accuracy and efficiency. The hybrid algorithm, *RCR* selects the same number of base stations as *BFS* for all the scenarios and is more accurate than *GEN*, *NGA* and *GRE*. The computational time of *RCR* is higher than *GRE* and *NGA* but remains feasible for practical applications. Thus, *RCR* has the potential to identify superior deployments efficiently without compromising accuracy. In Chapter 7, two more case studies are considered for the comparison of the five algorithms in different environments.

[11]The implementation details of the existing algorithms were discussed in Chapter 5.

Chapter 7

Comparison of Algorithms and Outline of Investigation

7.1 Introduction

In Chapter 5, four existing algorithms relevant to solving the indoor Base Station Placement (BSP) problem (namely the Brute Force Search (*BFS*), Genetic Algorithm (*GEN*), Greedy Algorithm (*GRE*) and Ngadiman's Algorithm (*NGA*)) were implemented and compared using Case Study 1. The results indicated that these algorithms provided an almost mutually exclusive tradeoff between *accuracy* and *efficiency*. In particular, *BFS* and *GEN* were observed to be accurate but not very efficient whereas *GRE* and *NGA* were efficient but not accurate. Therefore, in Chapter 6, a new hybrid algorithm, ***RCR*** ***(R****eduction Estimation* followed by ***C****ombinatorial Optimisation* either alone or in conjunction with ***R****eduction Approximation)* was proposed to combine the advantages of the existing algorithms i.e. have high *accuracy* (like *BFS* and *GEN*) and high *efficiency* (like *GRE* and *NGA*). *RCR* was also applied to Case Study 1 and it was observed that *RCR* provided superior results without sacrificing *accuracy* and *efficiency*.

Case Study 1 assumed free space propagation to find the distance dependent path loss values. In this chapter, two more case studies (Case Studies 2 and 3) are considered which are based on the path loss values found by in-building experimental measurements. Thus, the first aim of this chapter is to compare the five algorithms (*BFS, GEN, GRE, NGA* and *RCR*) in a variety of environments. In Section 7.2, the five algorithms are compared using Case Studies 1, 2 and 3 to identify which is the most appropriate algorithm to solve the indoor BSP problem. The second aim of this chapter is to clearly outline the investigations in Chapters 8-11 of this thesis. In Chapters 8-10, the effects of three factors (namely call traffic variability, user mobility and call switching technologies) on the optimisation results of the BSP problem are investigated and in

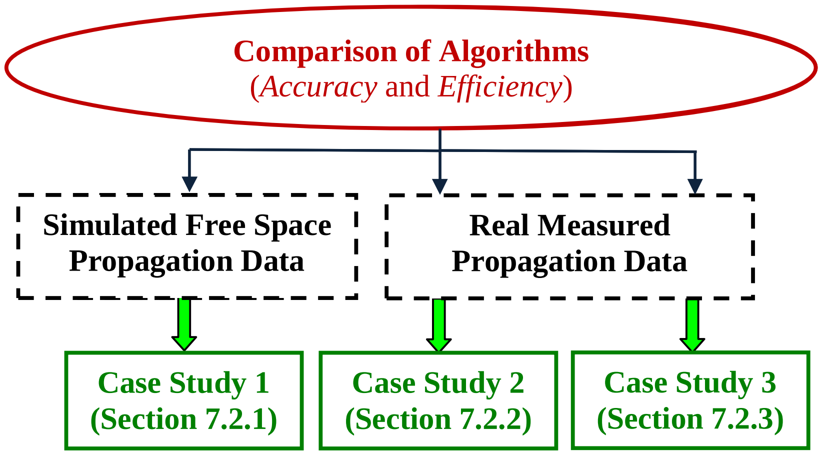


Figure 7.1: Outline of the Case Studies

Chapter 11, the BSP problem in multi-floored buildings is investigated. The investigations are outlined in Section 7.3. The chapter is summarised in Section 7.4.

7.2 Comparison of Algorithms

An algorithm is judged by its *accuracy* and *efficiency* [66, p3]. For the BSP problem, the algorithm which selects a smaller number of base stations (satisfying all the constraints) is considered to be more accurate and the algorithm which takes less computational time (to propose a solution) is considered to be more efficient. In Chapters 5 and 6, the *accuracy* and *efficiency* of the four existing algorithms (*BFS, GEN, GRE* and *NGA*) and the hybrid algorithm *(RCR)* were compared using a simple case study (Case Study 1).

In this section, the results of Case Study 1 are summarised and two new case studies (Case Studies 2 and 3) are presented to compare the *accuracy* and *efficiency* of the five algorithms in a variety of environments. As shown in Fig. 7.1, free space propagation is assumed (for simplicity) in Case Study 1. In Case Studies 2 and 3, propagation data measured[1] in real environments is used.

7.2.1 Case Study 1

Case Study 1 was used for comparison of the five algorithms in Chapter 5 (Section 5.3) and Chapter 6 (Section 6.3), where the details of the physical environment and the results were

[1]The measurement campaigns (to measure the average path loss between the potential base station sites and user locations) were carried out in several buildings at The University of Auckland and are described in Appendix A [5, 24].

discussed. A summary is presented here for convenience in comparing the performances of the five algorithms for the three case studies.

Physical Environment

The floor layout for Case Study 1 is shown in Fig. 5.8. The problem definition is identical to that in Section 5.3.1.

Results and Discussion

As discussed in Section 5.3.3 and Section 6.3.3, the four existing algorithms provide an almost mutually exclusive tradeoff between *accuracy* and *efficiency*. The hybrid algorithm, *RCR* identifies superior deployments without significantly compromising *accuracy* and *efficiency*.

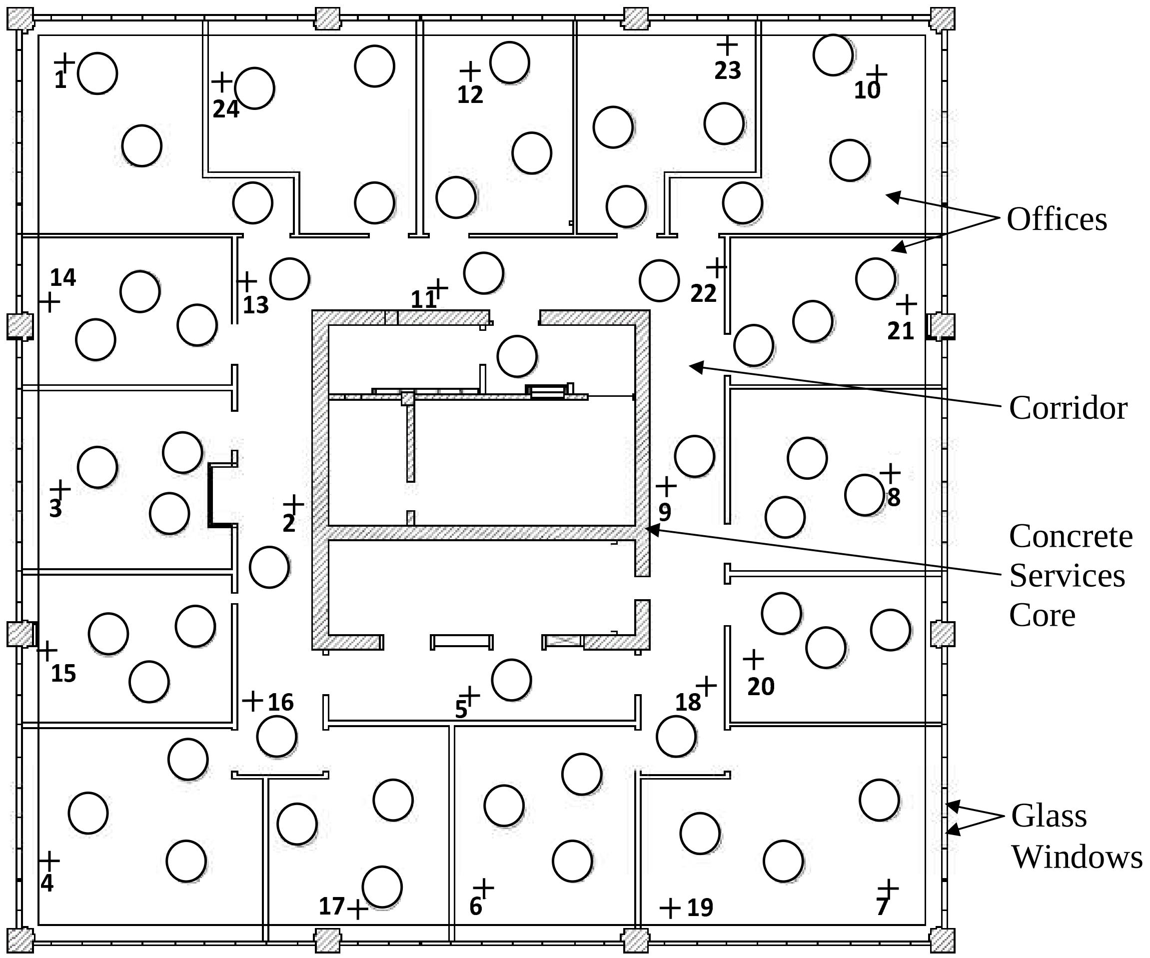
The path loss estimates for Case Study 1 are found assuming free space propagation. Case Study 1 was contrived for ease of implementation and to permit an initial assessment of performance. Now two more case studies (Case Studies 2 and 3), with path loss values found by in-building experimental measurements, are considered for the comparison of the five algorithms.

7.2.2 Case Study 2

Physical Environment

The floor layout (with dimensions 18.5m $\times$ 18.5m) is shown in Fig. 7.2. The potential base station sites and user locations are indicated by (+) and ($\bigcirc$), respectively. The floor has a centrally located concrete services core (containing the lifts and stairwell) which is surrounded by a corridor. The corridor is in turn surrounded by offices.

The BSP problem is defined using the number of potential base station sites and user locations, path loss estimates, Call Admission Control (CAC) strategy and Grade of Service (GoS). As shown in Fig. 7.2, there are 24 potential base station sites (i.e. $N_{bs} = 24$) and 54 potential user locations (i.e. $N_u = 54$). The path loss values are found by in-building experimental measurements [5]. The CDMA Call Admission Control (CAC) strategy is used and the values of the CDMA parameters are the same as those used for Case Study 1 (shown in Table 5.1). Again, the Grade of Service (GoS) adopted is 2%, i.e. at most 2% of the total calls are lost (or the call failure rate $\leq 2\%$).



+ Potential base station site ○ Potential user location

Figure 7.2: Floor layout (18.5m × 18.5m) for Case Study 2.

Results and Discussion

Optimisation results are presented for five discrete scenarios[2] (corresponding to 15, 20, 25, 30 and 35 active users). For example, in the first scenario, it is assumed that 15 users are active in each trial. These users are selected (out of the 54 potential user locations) randomly for each trial. All the five algorithms are implemented for 500 different trials to find an overall optimal solution rather than finding a solution for one particular trial. The *accuracy* and *efficiency* of the algorithms are compared to identify the most appropriate algorithm to solve the indoor BSP problem.

Fig. 7.3 is in the same format as Fig. 6.4 and shows the results (i.e the number of base stations selected and the computational time (in kiloseconds, ks)) for Case Study 2. Ideally,

[2]Different scenarios are chosen because they represent a range of possible traffic conditions.

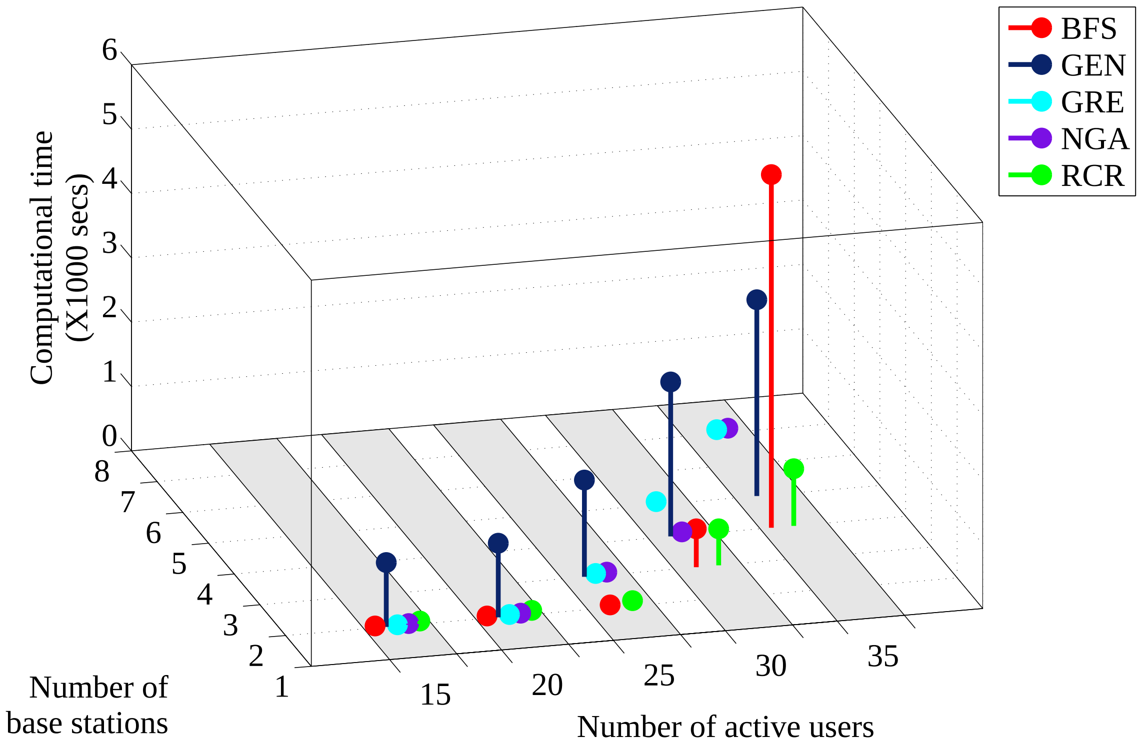


Figure 7.3: Comparison of *accuracy* (number of base stations selected) and *efficiency* (computational time) of the algorithms for the five scenarios (grey bars) of Case Study 2. All sticks in a given grey bar are the results (obtained by the five algorithms) for a particular scenario. The sticks are spatially separated to clearly show the results (i.e. without overlap). Ideally, an algorithm should select the least number of base stations (i.e. equal to the number of base stations selected by *BFS* (red sticks)), and have the shortest computational time (i.e. shortest stick height).

an algorithm should select the least number of base stations (i.e. equal to the number of base stations selected by *BFS* (red sticks)), and have the shortest computational time (i.e. shortest stick height).

The results observed for Case Study 1 and 2 are similar. Both *BFS* and *RCR* select the same minimum number of base stations to serve the users for all the scenarios and are the most accurate algorithms, followed by *GEN* (which selects an extra base station in some scenarios). *NGA* and *GRE* are highly inaccurate as they select up to three extra base stations for deployment. The computational time is least for *GRE* and *NGA* followed by *RCR*. However, both *BFS* and *GEN* have high computational times particularly for a high number of users. Thus, *RCR* is able to identify a deployment equivalent to *BFS* but in a significantly shorter time.

7.2.3 Case Study 3

Physical Environment

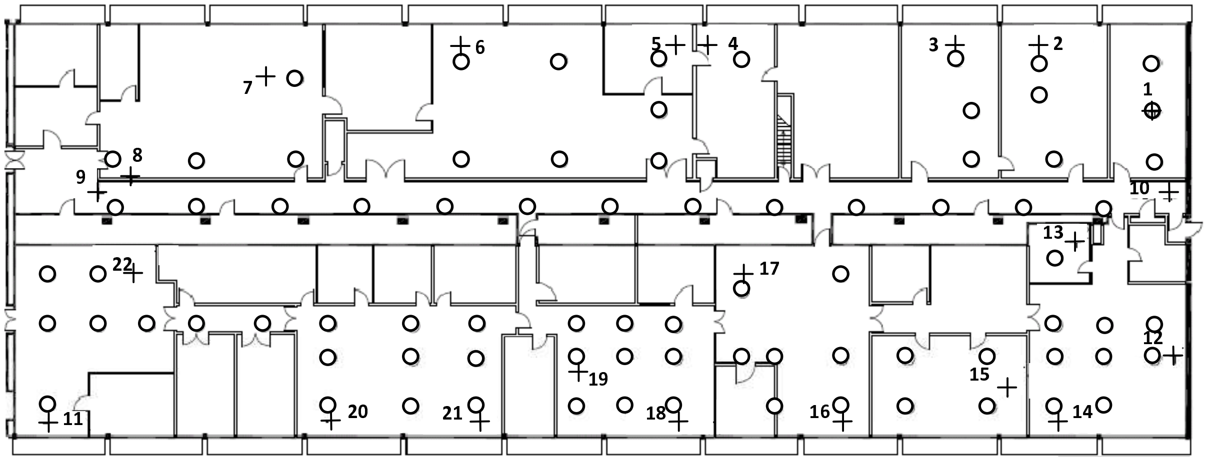
The floor layout (with dimensions 71m $\times$ 25m) is shown in Fig. 7.4. The potential base station sites and user locations are indicated by (+) and (○), respectively. The BSP problem is defined using the number of potential base station sites and user locations, path loss estimates, Call Admission Control (CAC) strategy and Grade of Service (GoS). As shown in Fig. 7.4, there are 22 potential base station sites (i.e. $N_{bs} = 22$) and 80 potential user locations (i.e. $N_u = 80$). The path loss values are found by in-building experimental measurements [5]. The CDMA Call Admission Control (CAC) strategy is used and the values of the CDMA parameters are the same as used for Case Studies 1 and 2 (shown in Table 5.1). Again, the Grade of Service (GoS) adopted is 2% i.e. at most 2%, of the total calls are lost (or the call failure rate $\leq 2\%$).

Results and Discussion

Optimisation results are presented for five discrete scenarios[3] (corresponding to 25, 30, 35, 40 and 45 active users). The active users are selected (out of the 80 potential user locations) randomly for each trial. All the five algorithms are again implemented for 500 different trials to find an overall optimal solution. The *accuracy* and *efficiency* of the algorithms are compared to identify the most appropriate algorithm to solve the indoor BSP problem.

Fig. 7.5 is in the same format as Figs. 7.3 and 6.4 and shows the results for Case Study 3. The results for Case Study 3 follow a similar trend to the results of Case Studies 1 and 2. Fig. 7.5 shows that *BFS* and *RCR* select the same minimum number of base stations in each scenario. Both *GEN* and *NGA* select the same number of base stations (up to two above the *BFS* result)

[3]Different scenarios are chosen because they represent a range of possible traffic conditions. Compared to the previous two Case Studies, more active users are chosen in this Case Study for better comparison of the algorithms.



+ Potential base station site   O Potential user location

Figure 7.4: Floor layout (71m $\times$ 25m) for Case Study 3.

in most scenarios except for the 30 active user scenario where *GEN* is more accurate than *NGA*. *GRE* is most inaccurate as it selects up to three extra base stations. The computational time is least for *GRE* and *NGA* and slightly higher for *RCR*. *BFS* and *GEN* have a very high computational time for a high number of active users. Thus, *RCR* again provides greater *efficiency* and *accuracy* in arriving at the results.

The performances of the five algorithms are found to be similar for Case Studies 1, 2 and 3 undertaken on three different layouts with dissimilar architecture and different propagation conditions. The comparison results of the five algorithms are summarised is Table 7.1. *BFS* and *GEN* are observed to be accurate but not very efficient whereas *GRE* and *NGA* are efficient but not accurate. *RCR* identifies optimal deployments without significantly compromising *accuracy* and *efficiency*. Thus, in Chapters 8-11 of this thesis, *RCR* will be applied (to Case Studies 2 and 3) to investigate the effect of different factors (which are discussed in the next section) on the BSP problem.

7.3 Outline of Investigation

There are several additional factors that can affect the optimal number and locations of base stations required to serve the users in indoor wireless communication systems. These include but are not limited to:

1. Call traffic variability [19, pp333-335] [23, pp161-166, 370] [70, pp208-209] [85, p229];

2. User mobility [4, p16] [16, p43] [23, pp164-165] [85, p229]; and

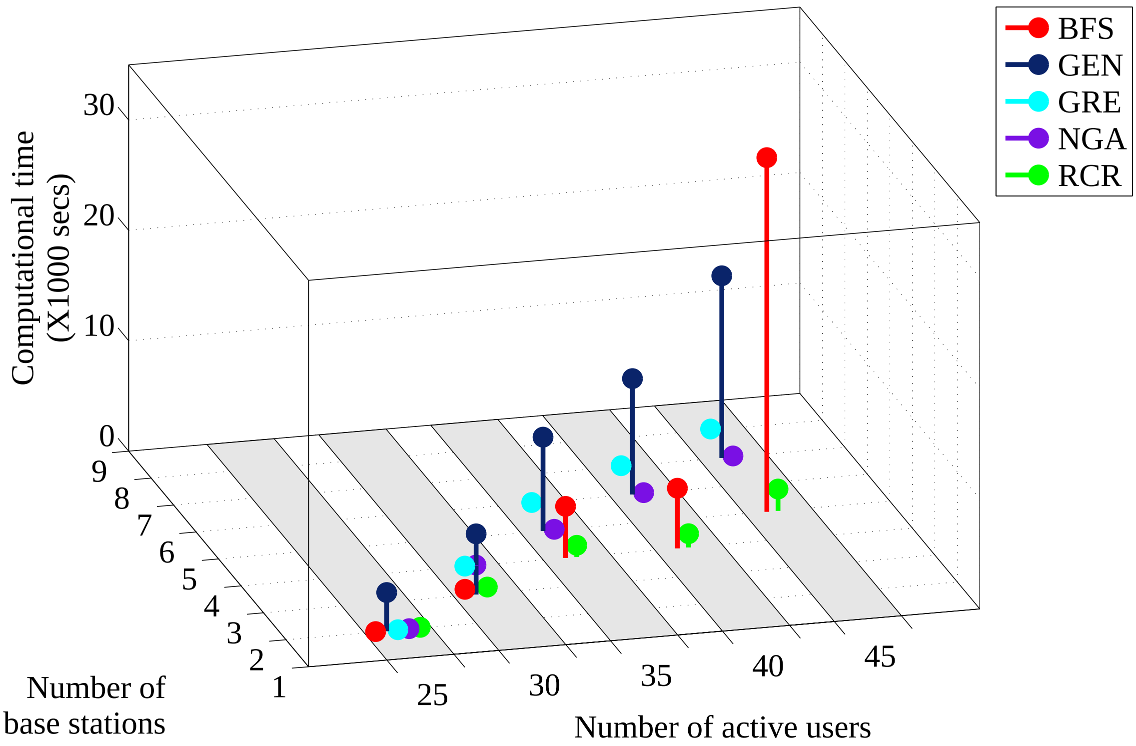


Figure 7.5: Comparison of *accuracy* (number of base stations selected) and *efficiency* (computational time) of the algorithms for the five scenarios (grey bars) of Case Study 3. All sticks in a given grey bar are the results (obtained by the five algorithms) for a particular scenario. The sticks are spatially separated to clearly show the results (i.e. without overlap). Ideally, an algorithm should select the least number of base stations (i.e. equal to the number of base stations selected by *BFS* (red sticks)), and have the shortest computational time (i.e. shortest stick height).

Algorithm	***Accuracy***	***Efficiency***	***Comment***
Brute Force Search (BFS)	✓✓	✗✗	Provides optimal solutions using exhaustive search. Unsuitable for problems other than those that are very simple.
Genetic Algorithm (GEN)	✓	✗	Provides good approximate (but not optimal) solutions for practical problems.
Greedy Algorithm (GRE)	✗✗	✓✓	Provides fast estimates but not optimal solutions. Easy to implement.
Ngadiman's Algorithm (NGA)	✗	✓✓	Provides fast and approximate (but not optimal) solutions.
Reduction Estimation — Combinatorial Optimisation — Reduction Approximation (RCR)	✓✓	✓	Provides optimal solutions in practical time.

Table 7.1: Comparison of *accuracy* and *efficiency* of the five algorithms for Case Studies 1, 2 and 3.

3. Call switching technologies [19, pp333-342] [70, p212] [85, pp217-218].

In Chapters 8-10 of this thesis, the effects of the three factors (i.e. call traffic variability, user mobility and call switching technologies) on the optimisation results of the Base Station Placement (BSP) problem are investigated. Call traffic refers to the variations in call arrivals and departures. In this thesis, two options are considered for call traffic — static and dynamic. Call traffic is considered to be static when the users have no variations in call arrivals and departures and all the users try to connect to the base stations at the same time. On the other hand, call traffic is considered to be dynamic when the users have variations in call arrivals and departures over a period of time and try to connect to the base stations only when a call arrives. Similarly, as shown in Fig. 7.6, two options are considered for each of the three factors. The users can be either fixed (i.e. no mobility) or moving throughout the call and the call switching technology can be either circuit or packet switched with different packet arrival distributions (as defined in Fig. 7.6).

The combinations of the three factors (with two options each) can model a range of indoor wireless communication systems. For example, there can be a system model (System Model A (S/F/C)) with static call traffic, fixed users and circuit switched calls or a system model (System Model B (D/F/C)) with dynamic call traffic, fixed users and circuit switched calls. Similarly, four system models (System Models A-D) are proposed to investigate the effects of the factors on optimisation. The details of the four models, System Model A (S/F/C), System Model B (D/F/C), System Model C (D/M/C) and System Model D (D/M/P) are shown in Table 7.2.

In any two consecutive models, the options of only one factor are different so that the effect of that factor on the optimisation results of the BSP problem can be investigated. For example, the only difference between System Models A (S/F/C) and B (D/F/C) is the call traffic (which is static in System Model A (S/F/C) and dynamic in System Model B (D/F/C)). Thus, the optimisation results of System Models A (S/F/C) and B (D/F/C) can be compared to investigate the effect of traffic variability on the BSP problem. Similarly, the optimisation results of System Models B (D/F/C) and C (D/M/C) can be compared to investigate the effect of user mobility and System Models C ((D/M/C) and D (D/M/P) can be compared to investigate the effect of call switching technologies on the BSP problem. Thus, the effects of the factors on the optimisation results of the BSP problem are investigated[4] in Chapters 8-10 using System Models A-D as shown in Fig. 7.7.

In Chapter 8, the implementations of System Models A (S/F/C) and B (D/F/C) are discussed to understand how static and dynamic call traffic variations are modelled. The optimisation

[4]The investigation is performed by applying *RCR* to the physical environments of Case Studies 2 and 3 (described in Sections 7.2.2 and 7.2.3)

Factor	*Options*	*Definition*
Call Traffic	**Static**	Users have no variations in call traffic (i.e. call arrivals and departures) and all the users try to connect to the base stations at the same time.
	Dynamic	Users have variations in call traffic over a period of time and try to connect to the base stations only when a call arrives.
User Mobility	**Fixed**	Users are fixed and remain at their original location on the floor during the calls.
	Moving	Users are moving on the floor during the calls with predefined or random mobility profiles.
Call Switching Technology	**Circuit**	User calls are circuit switched i.e. each user establishes a dedicated connection to a base station during a call.
	Packet	User calls are packet switched i.e. the users connect to a base station only when they have to send packets during a call. The packets traffic can be either Constant Bit Rate (CBR) or Variable Bit Rate (VBR).

Figure 7.6: Factors affecting BSP in indoor wireless communication systems.

System Model	Call Traffic (Static/Dynamic)	User Mobility (Fixed/Moving)	Call Switching Technology (Circuit/Packet)
System Model A (S/F/C)	Static	Fixed	Circuit
System Model B (D/F/C)	Dynamic	Fixed	Circuit
System Model C (D/M/C)	Dynamic	Moving	Circuit
System Model D (D/M/P)	Dynamic	Moving	Packet

Table 7.2: System Models representing different combinations (of the options) of the factors affecting BSP.

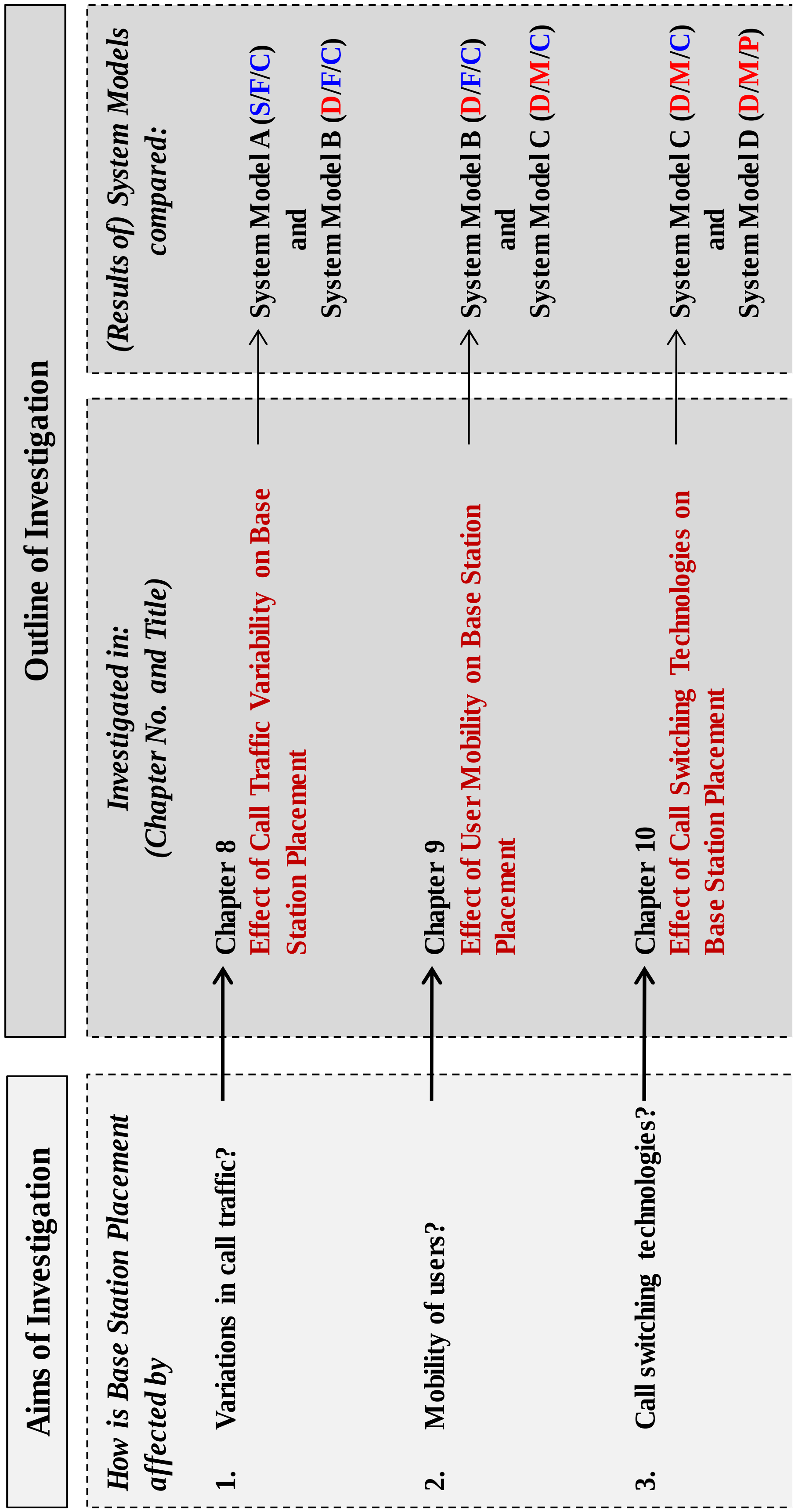


Figure 7.7: Aims and Outline of Investigation.

results of System Models A and B are compared to investigate the effect of traffic variability on the BSP problem.

In Chapter 9, the implementation of System Model C (D/M/C) is discussed to understand how mobility of indoor users is modelled. The optimisation results of System Models B and C are compared to investigate the effect of user mobility on the BSP problem.

In Chapter 10, the implementation of System Model D (D/M/P) is discussed to understand how packet switched systems and different packet arrival distributions are modelled. The optimisation results of System Models C and D are compared to investigate the effect of call switching technologies on the BSP problem.

In Chapter 11, the BSP problem is extended to multi-floored buildings and potential areas for future work are identified. Finally, the key conclusions of this thesis are presented in Chapter 12.

7.4 Summary

In this chapter, the five algorithms proposed in Chapters 5 and 6 have been compared using three different case studies and the outline of investigations in Chapters 8-11 has been discussed. The three case studies (Case Studies 1, 2 and 3) are chosen so that the algorithms can be compared in different environments. The path loss estimates for Case Study 1 are found assuming free space propagation and for Case Studies 2 and 3 are found by in-building experimental measurements.

The five algorithms (*BFS, GEN, GRE, NGA* and *RCR*) are compared (using the three case studies) in terms of accuracy and efficiency. The performances of the five algorithms are observed to be similar for Case Studies 1, 2 and 3. In particular, *BFS* and *GEN* are accurate but not very efficient whereas *GRE* and *NGA* are efficient but not accurate. *RCR* identifies optimal deployments, without significantly compromising accuracy and efficiency, for all the three case studies. Thus, in Chapters 8-11 of this thesis, *RCR* will be used to investigate the effect of different factors on the BSP problem.

In Chapters 8-10, the effects of the three factors (i.e. call traffic, user mobility and call switching technologies) on BSP are investigated. Each factor can have two options — call traffic can be static or dynamic, users can be fixed (i.e. no mobility) or moving and call switching technology can be circuit or packet switched. Four system models, System Model A (S/F/C), System Model B (D/F/C), System Model C (D/M/C) and System Model D (D/M/P) are proposed with different combinations of the options. In Chapter 8, System Models A and B are used to investigate the effect of call traffic variability on the BSP problem. In Chapter 9, System Models B and C are used to investigate the effect of user mobility on the BSP problem. In Chapter 10, System Models C and D are used to investigate the effect of call switching technologies on the BSP problem. In Chapter 11, the BSP problem is extended to multi-floored buildings and potential areas for future work are identified. The main conclusions of this thesis are presented in Chapter 12.

Chapter 8

Effect of Call Traffic Variability on Base Station Placement

8.1 Introduction

In Chapter 7 (Section 7.3), three factors (i.e. call traffic variability, user mobility and call switching technologies) affecting Base Station Placement (BSP) were discussed and the two options for each factor were described — call traffic can be static or dynamic, users can be fixed or moving and call switching technology can be circuit or packet switched. Then, four system models[1], System Model A (S/F/C), System Model B (D/F/C), System Model C (D/M/C) and System Model D (D/M/P) were proposed so that the effects of the three factors on the optimisation results of the BSP problem can be investigated[2].

The aim of this chapter is to investigate the effect of call traffic variability on the BSP problem. The investigation is performed using System Models A (S/F/C) and B (D/F/C) which were proposed with different call traffic options. In Section 8.2, the implementations of System Models A and B are discussed to understand how static and dynamic call traffic are modelled for indoor users. Then, in Section 8.3, optimisation results[3] for System Models A and B are compared to investigate the effect of call traffic variability on the BSP problem. The chapter is summarised in Section 8.4.

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[1]The details of the System Models A-D are shown in Table 7.2.
[2]The outline of investigation is shown Fig. 7.7.
[3]Optimisation results are obtained by applying System Models A and B to case studies.

System Model	Call Traffic (Static/Dynamic)	User Mobility (Fixed/Moving)	Call Switching Technology (Circuit/Packet)
System Model A (**S**/**F**/**C**)	**Static**	**Fixed**	**Circuit**
System Model B (**D**/**F**/**C**)	**Dynamic**	**Fixed**	**Circuit**

Table 8.1: System models for investigating the effect of call traffic variability on BSP.

8.2 System Models for Call Traffic Variability

In a wireless communication system, calls can be considered to arrive, remain in the system for some duration and then depart. As shown in Fig. 7.6, in this thesis, two options are considered for call traffic — static and dynamic and two systems models (System Models A and B) are proposed to investigate the effect of call traffic variability on BSP.

8.2.1 System Model A (S/F/C)

As shown in Table 8.1, System Model A (S/F/C) represents a system with static call traffic, fixed users and circuit switched calls.

Static Traffic

Call traffic is termed static when the users have no variations in call arrivals and departures. In other words, static traffic represents a 'snapshot' of the system with a number of users (denoted as 'active' users) trying to connect to the base stations at an instant of time [23, p162] [70, p208]. For example, if there is a system with static traffic and N_{active} active users, it means that all the N_{active} users are trying to connect to the base stations at the same time.

In this thesis, System Model A is implemented for 500 different trials to find an overall optimal BSP rather than finding a solution for one particular trial (or arrangement of active users). As shown in Fig. 8.1, *call schedules* are generated for each trial with a unique set of N_{active} users. The locations of the N_{active} users are chosen randomly from the total number of potential user locations, N_u for each trial.

Fixed Users

As the system model represents the system at an instant of time, the user locations are fixed (i.e. no mobility) while the users try to connect to the base stations. In this thesis, the N_u potential

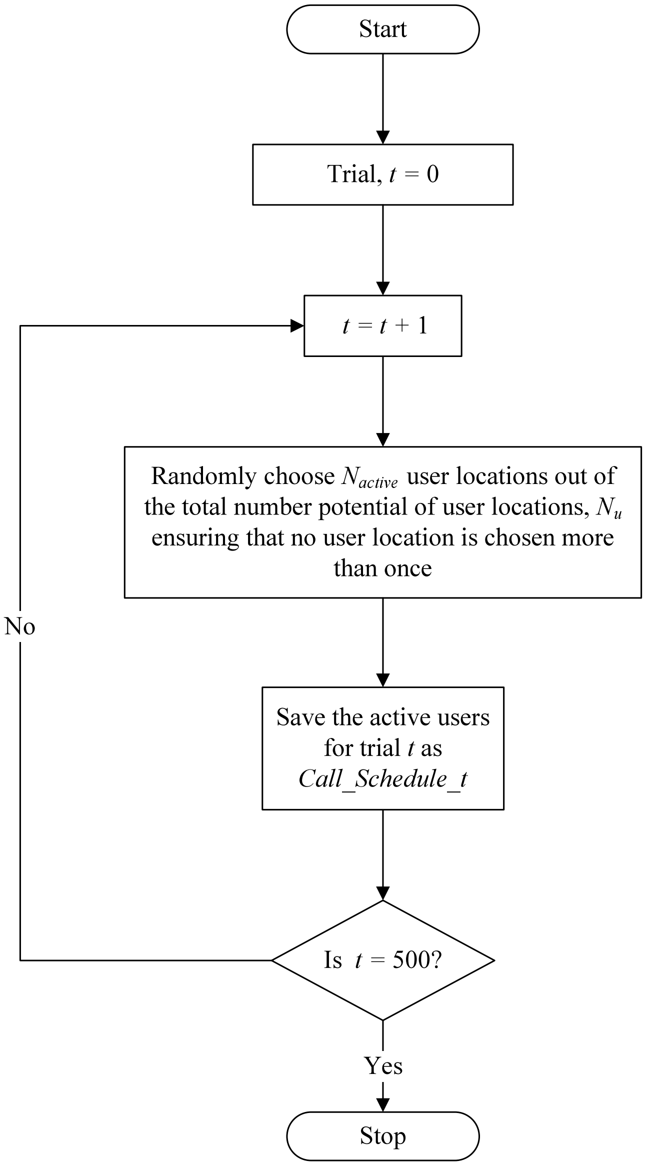


Figure 8.1: Generation of call schedules for static call traffic.

user locations are assumed to be fixed and therefore, the N_{active} active user locations (chosen from the potential user locations) are also fixed.

Circuit Switched Calls

The user connection is circuit switched, i.e. the user establishes a dedicated connection to the base station [18, p667] [19, p333]. In the implementation of System Model A, when an active user (in a trial) connects to a base station, it remains connected while the other active users try to connect to the base stations. Each trial is treated independently i.e. all the active users from the previous trials are disconnected before the next trial begins.

8.2.2 System Model B (D/F/C)

As shown in Table 8.1, System Model B (D/F/C) represents a system with dynamic call traffic, fixed users and circuit switched calls.

Dynamic Traffic

Call traffic is termed dynamic when the users have variations in call arrivals and departures. The users try to connect to the base stations when calls arrive and each user remains connected for the duration of its call [23, p162] [70, p208] [86, pp88-92]. As shown in Fig. 8.2, calls arrive and depart in the system at non-uniform time intervals and a call that arrives before another call can depart later. For example, in Fig. 8.2, Call 1 arrives before Calls 2 and 3 but departs after Calls 2 and 3.

The dynamic call traffic, A (measured in Erlangs) is given by

$$A = \lambda \times \mu \tag{8.1}$$

where λ is the mean call arrival rate (i.e. the average number of calls per unit time) and μ is the mean call duration (i.e the difference between arrival and departure times of the call) [4, pp221-222] [69, p166]. For example, if a group of users make 60 calls in one hour, and each call has a mean call duration of 3minutes, then the call traffic

$$A = 60 \times \frac{3}{60} = 3 \text{ Erlangs.}$$

Similarly, if a user makes 1 call in one hour with a mean call duration of 60minutes, the call traffic, $A = 1 \times \frac{60}{60} = 1$ Erlang.

In this thesis, it is assumed that the dynamic call traffic follows an Erlang distribution, which has the following assumptions [4, pp221-232] [11, p77] [87, p14] [88, p97]:

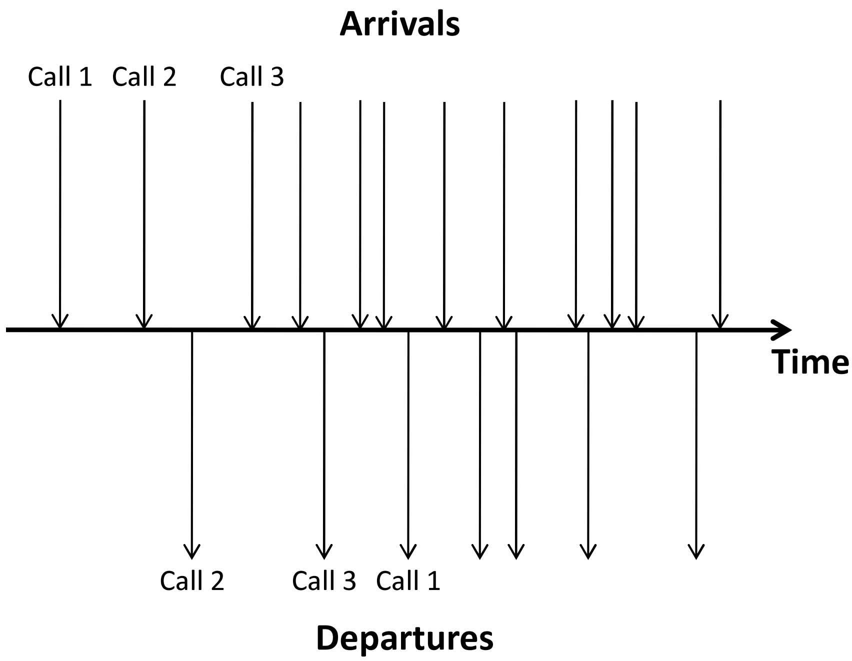


Figure 8.2: Call arrivals and departures over time.

- The call arrivals follow a Poisson distribution. Poisson arrivals mean that the time between call arrivals (inter-arrival times) follow a Negative Exponential distribution;
- The call durations follows a Negative Exponential distribution; and
- The blocked calls are cleared from the system.

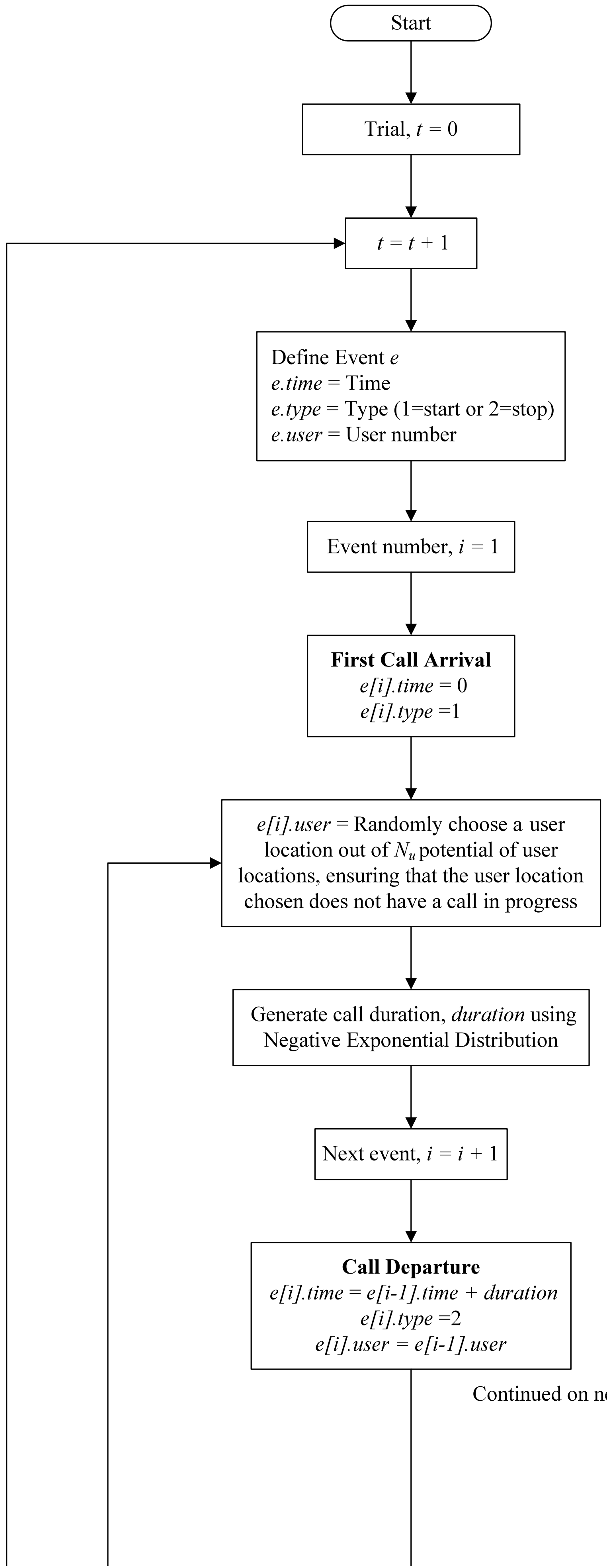
System Model B is implemented by generating call schedules for 501 different trials[4] to find an overall optimal BSP rather than finding a solution for one particular trial. Each trial represents call arrivals and departures in one busy hour[5] (and the total time of the trial is 3600s). As shown in Fig. 8.3, call schedules are generated for each trial with a unique set of events.

Each event, *e* has three parts, namely

1. *e.time*: Time at which the event occurs. The value can be between 0 and 3600s.
2. *e.type*: Type of the event. The value can be either 1 or 2 depending on if the event is the starting (arrival) of a new call or stopping (departure) of an existing call, respectively.
3. *e.user*: User number for the event (i.e. the user location at which the event occurs). The value can be between 1 and N_u, the total number of potential user locations.

[4]One extra trial is implemented because the first trial is used as a ‘warm up’ period to prepare the system. The results of the first trial are excluded from the call failure rate statistics.

[5]The trials are performed in continuity and the active calls at the end of each trial/busy hour are transferred to the next trial.



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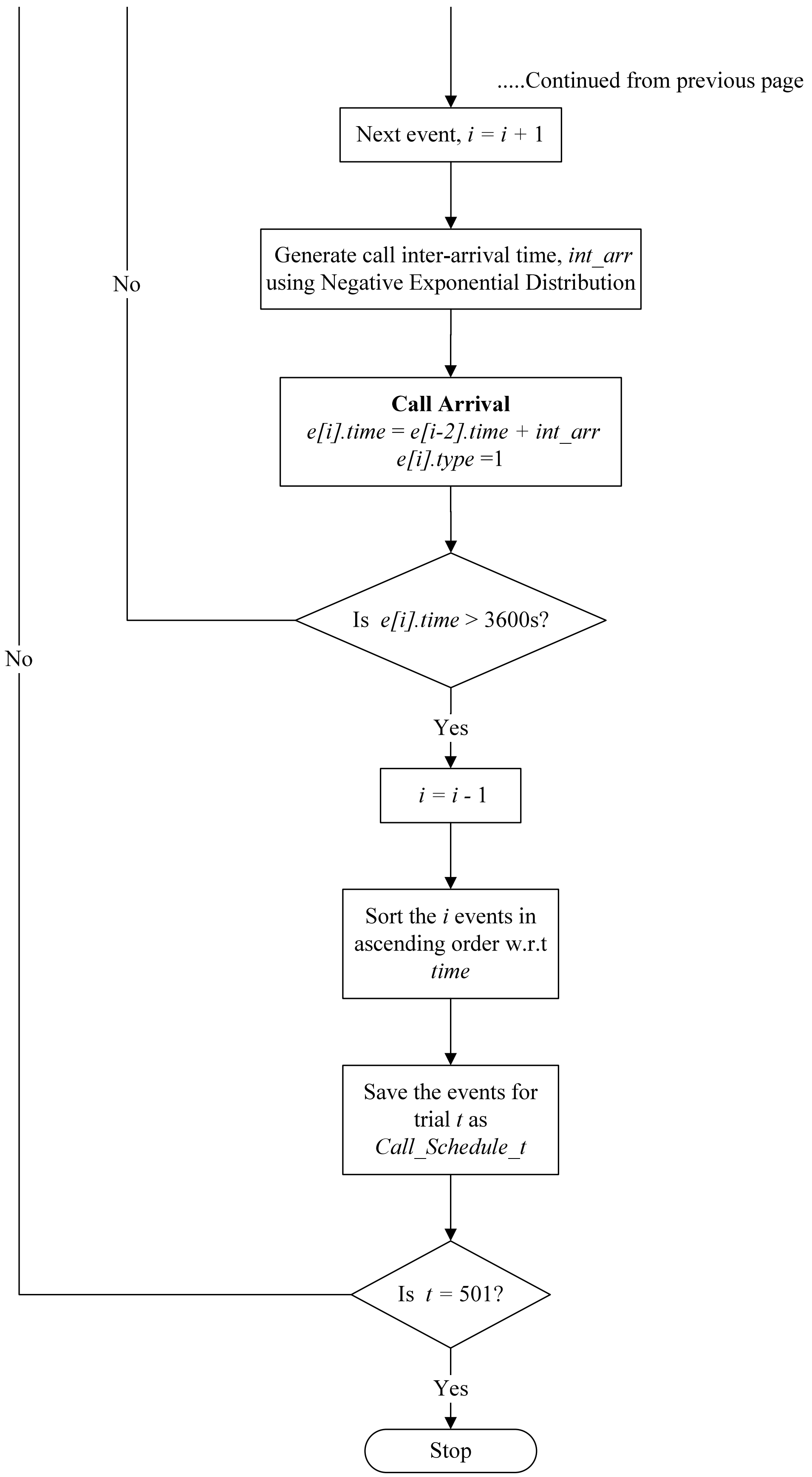


Figure 8.3: Generation of call schedules for dynamic call traffic.

For each trial, the first event is the **first call arrival.** The user location for the event is chosen randomly. Then, the *duration* of the arrived call is generated[6]. The next event is the **call departure** event for the arrived call. The call departure time is calculated by adding the call arrival time and the *duration*. Then, the time between call arrivals, *int_arr* is generated[7]. The next event is the **call arrival** event for a new call. The call arrival time is calculated by adding the call arrival time of the previous call and *int_arr*. Then, the user location for the call arrival is chosen and another call departure event (corresponding to this call) is created. The process of creating call arrival and call departure events continues until the call arrival *time* is less than one hour (3600s). Finally, the events are arranged in ascending order (w.r.t. the *time* of the event) for optimisation. During optimisation, if a call cannot be connected (i.e. call is blocked), the call is cleared from the system.

Fixed Users

In the implementation of System Model B, the users have dynamic call traffic but they have no mobility. The calls arrive (and depart) at the N_u potential user locations which are assumed to be fixed for all the trials.

Circuit Switched Calls

The user call is circuit switched i.e. the user establishes a dedicated connection to the base station for the duration of the call [18, p667] [19, p333]. In the implementation of System Model B, a user connects to a base station when a call arrives, remains connected to the base station during the call and disconnects only when the call departs.

System Models A (S/F/C) and B (D/F/C) both have fixed users and circuit switched calls but the call traffic is different. System Model A represents a system with static traffic and System Model B represents a system with dynamic traffic and the optimisation results of System Models A and B can be compared to investigate the effect of traffic variability on the BSP problem. Static call traffic (in System Model A) is easier and less time consuming to implement than dynamic call traffic (in System Model B). However, the aim is to investigate how the implementations of System Models A and B affect the optimisation results. Therefore, in the next section, two case studies have been considered to investigate the performance[8] of System Models A and B in different environments.

[6]The call duration is generated using a Negative Exponential random number generator with a predefined mean call duration.

[7]The arrival time between calls is generated using a Negative Exponential random number generator with a predefined mean inter-arrival time.

[8]The performance is investigated by comparing the optimisation results obtained by using the *RCR* algorithm, described in Chapter 6.

8.3 Effect of Call Traffic Variability on Base Station Placement

Case Studies 2 and 3, described in Chapter 7 (Section 7.2), are used to investigate the effect of traffic variability on the BSP problem, by comparing the number of base stations required to serve the static traffic in System Model A and dynamic traffic in System Model B.

8.3.1 Case Study 2

The floor layout is the same as shown in Fig. 7.2. The problem definition (i.e. the number of potential base station sites and user locations, path loss estimates, Call Admission Control (CAC) strategy and Grade of Service (GoS)) is identical to that in Section 7.2.2.

System Models A (S/F/C) and B (D/F/C) are implemented to compare the number of base stations required to serve the users. System Model A is implemented for five discrete scenarios[9] corresponding to 5, 10, 15, 20 and 25 active users whereas System Model B is implemented for five discrete scenarios corresponding to 5, 10, 15, 20 and 25 Erlangs of traffic[10].

Fig. 8.4 shows the optimisation results achieved by implementing System Models A and B. The results indicate that two base stations are required for all the scenarios of System Model A and the first two scenarios (5 and 10 Erlangs) of System Model B. Thus, the implementation of the two system models give the same optimisation results for small traffic scenarios.

As the traffic increases, more base stations are required for System Model B than System Model A. For example, as shown in Fig. 8.4, for the fourth scenario (20 active users or Erlangs of traffic), System Model A requires 2 base stations whereas System Model B requires 4 base stations. This is because there are a fixed number of active users in System Model A but variations of call arrivals and departures in System Model B. For example, in the fourth scenario, System Model A is implemented for 20 active users and therefore, the number of active users at any instant of time is 20. On the other hand, System Model B is implemented for 20 Erlangs of call traffic and therefore, the mean number of calls at any instant of time is 20 but the momentary number of calls varies[11] from 0 to 46. Table 8.2 shows the number of active users at any instant of time for static traffic (in System Model A) and the mean and maximum number of calls at any instant of time for dynamic traffic (in System Model B). Thus, more base stations are required for System Model B than System Model A to cope with the variable number of calls

[9]Results for additional scenarios are shown in Appendix B.

[10]As discussed in Section 8.2.2, 1 Erlang is equivalent to having 1 user call for 1 hour. Therefore, 5 Erlangs of traffic (in System Model B) is equivalent to having 5 user calls (for 1 hour) and can be compared to 5 active users (in System Model A).

[11]The values, 0 and 46, were obtained after implementing System Model B on Case Study 2.

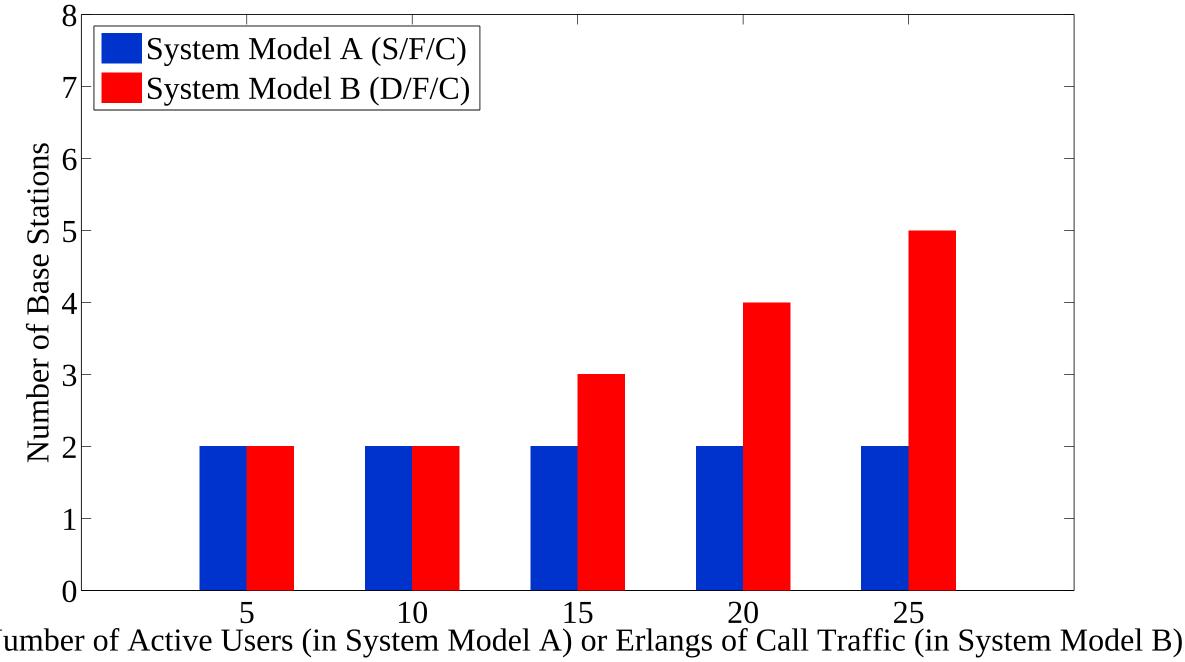


Figure 8.4: Optimisation results of System Models A (S/F/C) and B (D/F/C) for Case Study 2.

(in System Model B). Another case study (Case Study 3) is considered to check if similar results are achieved in a different environment.

8.3.2 Case Study 3

The Case Study 3 floor layout is shown in Fig. 7.4. The problem definition is identical to that in Section 7.2.3.

Fig. 8.5 shows the optimisation results achieved by implementing System Models A (S/F/C) and B (D/F/C). As shown in Fig. 8.5, System Models A and B are implemented for five discrete scenarios corresponding to 5, 10, 15, 20 and 25 active users and 5, 10, 15, 20 and 25 Erlangs of traffic, respectively. The results of Case Studies 2 and 3 follow a similar trend. As shown in Fig. 8.5, the implementations of the two system models again give the same optimisation results for small traffic scenarios. As the traffic increases, more base stations are required for System Model B than System Model A. For example, as shown in Fig. 8.5, for the fourth scenario, System Model A requires 2 base stations whereas System Model B requires 3 base stations. Again, this is because the call traffic is static in System Model A and dynamic in System Model B.

A real wireless communication system has variations in call arrivals and departures (i.e. dynamic traffic). Thus, the optimal BSP should be able to cope with dynamic traffic. In Case Studies 2 and 3 both, System Model A (S/F/C) required fewer base stations than System Model B (D/F/C) and if System Model A is used to find the optimal BSP, the system will be under

	System Model A	System Model B	
Scenario	No. of Active Users	Mean Number of Calls	Maximum Number of Calls
I	5	5	23
II	10	10	33
III	15	15	42
IV	20	20	46
V	25	25	54

Table 8.2: Number of active users (in System Model A) and mean and maximum number of calls (in System Model B) at any instant of time.

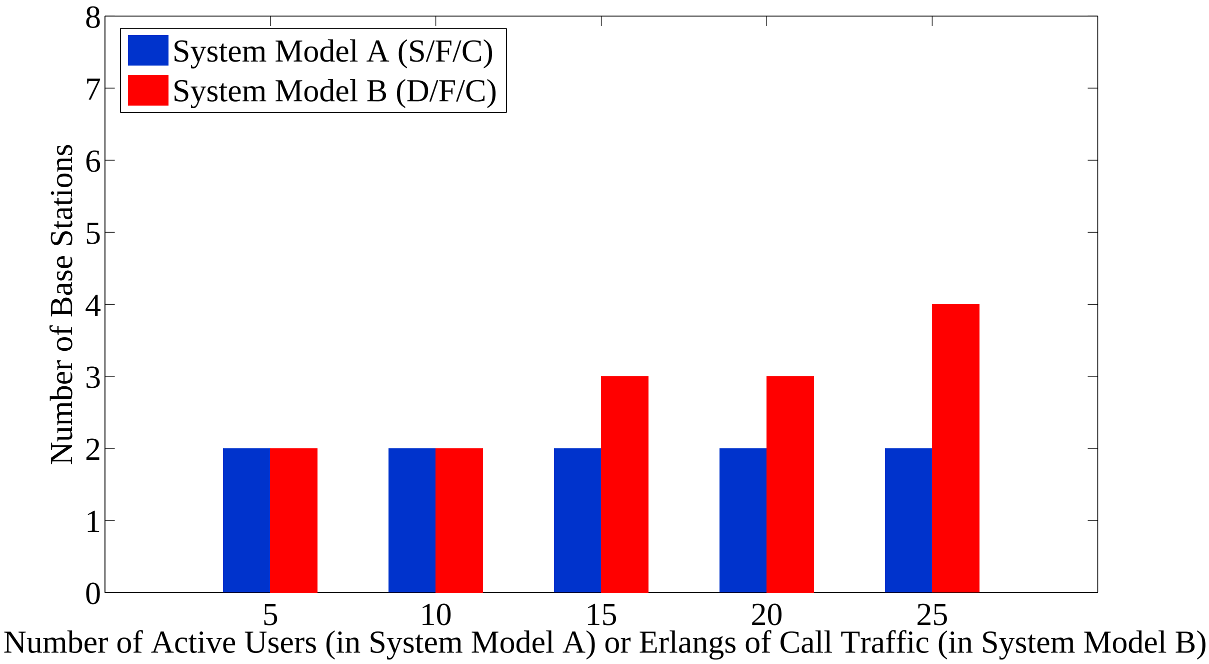


Figure 8.5: Optimisation results of System Models A (S/F/C) and B (D/F/C) for Case Study 3.

designed and will not be able to cope with high traffic. Even though System Model A is easier to implement, it is not sufficient for finding the optimal BSP that will achieve the required GoS for a real system. *Thus, dynamic call traffic must be considered for finding the optimal BSP.*

As the aim of this chapter was to investigate the effect of call traffic on BSP, fixed user locations were assumed for System Models A and B. In the next chapter, the effect of mobility on BSP is investigated using System Model B and a new system model, System Model C (D/M/C).

8.4 Summary

In this chapter, the effect of call traffic variability (i.e. variations in call arrivals and departures) on BSP has been investigated. Two system models, System Models A (S/F/C) and B (D/F/C) are defined and implemented for the investigation. System Model A represents a system with static call traffic, fixed users and circuit switched calls whereas System Model B represents a system with dynamic call traffic, fixed users and circuit switched calls. In System Model A, all the active users try to connect to the base stations at the same time and there are no variations of call traffic. In System Model B, the users have variations in call arrivals and departures and try to connect to the base stations only when a call arrives.

The effect of call traffic variability on the BSP problem is investigated by comparing the number of base stations required to serve the static traffic in System Model A and dynamic traffic in System Model B. The number of base stations required by System Models A and B is same for small traffic scenarios (5 and 10 Erlangs). However, for high traffic scenarios (15, 20 and 25 Erlangs), System Model A required fewer base stations than System Model B. This is because System Model A is implemented for a fixed number of users whereas System Model B is implemented for variable number of calls. A real wireless communication system has variations in call arrivals and departures (i.e. dynamic traffic). BSP found considering static traffic will under design the system and will not achieve the required GoS for a real system. Therefore, dynamic call traffic must be considered for finding the optimal BSP. In the next chapter, the effect of mobility on BSP is investigated using System Models B (D/F/C) and C (D/M/C).

Chapter 9

Effect of User Mobility on Base Station Placement

9.1 Introduction

In Section 7.3, three factors (i.e. call traffic variability, user mobility and call switching technologies) affecting Base Station Placement (BSP) were discussed and the two options for each factor were described. As shown in Fig. 7.6, call traffic can be static or dynamic, users can be fixed or moving and call switching technology can be circuit or packet switched. Then, four system models[1], System Models A-D were proposed to investigate[2] the effects of the three factors on the optimisation results of the BSP problem. In Chapter 8, the effect of call traffic variability on BSP was investigated using System Models A and B.

The aim of this chapter is to investigate the effect of user mobility on the BSP problem. The investigation is performed using System Models B (D/F/C) and C (D/M/C) which were proposed with different user mobility options. In Section 9.2, the implementations of System Models B and C are discussed to understand how mobility of indoor users is modelled. Then, in Section 9.3, optimisation results[3] for System Models B and C are compared to investigate the effect of user mobility on the indoor BSP problem. Section 9.4 presents a summary of the chapter.

[1]The details of the four system models, System Model A (S/F/C), System Model B (D/F/C), System Model C (D/M/C) and System Model D (D/M/P) are shown in Table 7.2.

[2]The outline of investigation is shown Fig. 7.7.

[3]Optimisation results are obtained by applying System Models B and C to case studies.

System Model	Call Traffic (Static/Dynamic)	User Mobility (Fixed/Moving)	Call Switching Technology (Circuit/Packet)
System Model B (D/F/C)	Dynamic	Fixed	Circuit
System Model C (D/M/C)	Dynamic	Moving	Circuit

Table 9.1: System Models for investigating the effect of user mobility on BSP.

9.2 System Models for User Mobility

Table 9.1 shows the two system models (System Models B and C) proposed with different options of user mobility.

9.2.1 System Model B (D/F/C)

As shown in Table 9.1, System Model B (D/F/C) represents a system with dynamic call traffic, fixed users and circuit switched calls. The details of System Model B are the same as discussed in Section 8.2.2 and are summarised in this section.

Dynamic Traffic

Call traffic is termed dynamic when the users have variations in call arrivals and departures over time [86, pp88-92]. Each user tries to connect to a base station when a call arrives and remains connected for the duration of its call [70, p208]. In this thesis, it is assumed that the dynamic call traffic follows an Erlang distribution, which has the following assumptions [4, pp221-232] [11, p77]:

- The call arrivals follow a Poisson distribution. Poisson arrivals mean that the time between call arrivals (inter-arrival times) follow a Negative Exponential distribution;
- The call durations follow a Negative Exponential distribution; and
- The blocked calls are cleared from the system.

System Model B is implemented by generating call schedules for 501 different trials[4], as discussed in Section 8.2.2 (and shown in Fig. 8.3). Each trial represents call arrivals and departures in one busy hour (with a total time of 3600s).

[4]The first trial is used as a 'warm up' period to prepare the system. The results of the first trial are excluded from the call failure rate statistics.

Fixed Users

In the implementation of System Model B, the users have no mobility. The calls arrive (and depart) at the N_u potential user locations which are assumed to be fixed for all the trials.

Circuit Switched Calls

In the implementation of System Model B, the user call is circuit switched i.e. the user connects to a base station when a call arrives, remains connected to the base station during the call and disconnects only when the call departs [19, p333].

9.2.2 System Model C (D/M/C)

As shown in Table 9.1, System Model C (D/M/C) represents a system with dynamic call traffic, moving users and circuit switched calls.

Dynamic Traffic

Call traffic is termed dynamic when the users have variations in call arrivals and departures over time [86, pp88-92]. The assumptions and call schedules for the dynamic call traffic in System Model C are identical to System Model B. Thus, it is assumed that call traffic follows an Erlang distribution [11, p77]. Call schedules are generated for 501 different trials to find an overall optimal BSP and each trial represents call arrivals and departures in one busy hour. The details of generation are discussed in Section 8.2.2 (and shown in Fig. 8.3).

Moving Users

In the implementation of System Model C, the users have mobility i.e. they can physically move while receiving dynamic calls. Though the mobility of the users can be modelled using many deterministic and random models, a more popular model is the Random Waypoint model, wherein the mobility paths and the speeds of the users are chosen randomly [16, p43], [85, p229], [89, p53], [90–93].

In this thesis, the user mobility is assumed to follow the Random Waypoint model. The total number of potential users (N_u) are divided into two categories — Office Bearers (N_{u_o}) and Visitors (N_{u_v}). A mobility profile (i.e. a set of locations for every second during the busy hour) is generated for each user, depending on the category of the user.

Office Bearers are the users who work in the offices on the floor and thus, spend most of their time at a fixed location inside their office. However, to include mobility, it is assumed that each user leaves his/her office once during the busy hour and returns back to the office. Fig. 9.1 shows how the mobility profiles for office bearers are generated. The location (at each second of time, *t*), *loc[t]* of an office bearer is assumed to be his/her *office* during the busy hour. As the user leaves the office once during the busy hour, the ***starting time*** and the ***destination*** are chosen randomly. The starting time, *s_time* is the time when the user leaves the office and can have a value between 0 and 3600s. The destination is the office visited by the user and can be any office except the user's own office. Then, the ***direction*** of travel is chosen (based on the floor layout and the locations of the user's office and the destination) and the *distance* (of travel) is calculated. Then, the ***velocity*** is chosen randomly, out of four possible values — 0.5m/s, 1m/s, 1.5m/s or 2m/s and the travel time, *t_time* is calculated. The locations, *loc[t]* of the user for the *t_time* are calculated. Then, the value of the ***waiting time***, *w_time* (i.e. the time that the user spends at the destination) is chosen (randomly) between 0 and 15minutes (900s). The location of the user for the *w_time* is the location of the destination. After the *w_time,* the user returns to his/her own office backtracking along the same path. The velocity is chosen again and the new travel time, *t_time* and locations, *loc[t]* of the user for the *t_time* are calculated. Finally, the set of locations is saved as the *mobility profile* of the user. The process is repeated for all the users that are office bearers.

Visitors are the users who come from outside to visit the office bearers. The visitors start their travel from either the entrance or an office (where they went before the busy hour). The visitors are assumed to be on the floor for the entire busy hour and can visit multiple office bearers. Fig. 9.2 shows how the mobility profiles for visitors are generated. The user starts from the ***origin*** (chosen from either the *entrance* or an *office*). Thus, the location (at the starting time), *loc[t]* of the visitor is the origin. Then, the ***destination*** (i.e. the office visited by the user) is chosen randomly. Then, the ***direction*** of travel is chosen (based on the floor layout and the locations of the user's origin and the destination) and the *distance* is calculated. Then, the ***velocity*** is chosen randomly, out of four possible values — 0.5m/s, 1m/s, 1.5m/s or 2m/s. The travel time, *t_time* and the locations, *loc[t]* of the user for the *t_time* are calculated. Then, the value of the ***waiting time***, *w_time* is chosen (randomly) between 0 and 30minutes (1800s). The location of the user for the *w_time* is the location of the destination. After *w_time,* the user repeats the process by choosing another destination, direction, velocity and waiting time and calculating the locations. The process continues for the hour (i.e. until the starting time of the process is less than 3600s). Then, the set of locations is saved as the *mobility profile* of the user. The whole process is repeated to generate mobility profiles for all the users that are visitors.

In this thesis, a user (office bearer or visitor) follows its mobility profile at all times but tries to connect to a base station only when a call arrives. The connection of the user is checked[5] at every second for the duration of the call. If the connection is satisfactory, the user continues to remain connected to the current base station otherwise it tries to connect to a new base station. If the user is unsuccessful in finding a new base station, the call is dropped. If the user finds a new base station, *soft handover*[6] is performed and the call continues.

Circuit Switched Systems

In the implementation of System Model C, the user call is circuit switched i.e. the user establishes a dedicated connection to a base station when a call arrives and disconnects when the call departs [19, p333].

System Models B (D/F/C) and C (D/M/C) both have dynamic traffic and circuit switched calls but the user mobility is different. System Model B represents a system with fixed users and System Model C represents a system with moving users and thus, the optimisation results of System Models B and C can be compared to investigate the effect of user mobility on the BSP problem. System Model B is easier and less time consuming to implement than System Model C because the mobility profiles and handover are not considered in System Model B. However, the aim is to investigate how the implementations of System Models B and C affect the optimisation results. Therefore, in the next section, two case studies have been considered to investigate the performance[7] of System Models B and C in different environments.

9.3 Effect of User Mobility on Base Station Placement

Case Studies 2 and 3, described in Chapter 7 (Section 7.2), are used to investigate the effect of user mobility on the BSP problem, by comparing the number of base stations required to serve the fixed users in System Model B and moving users in System Model C.

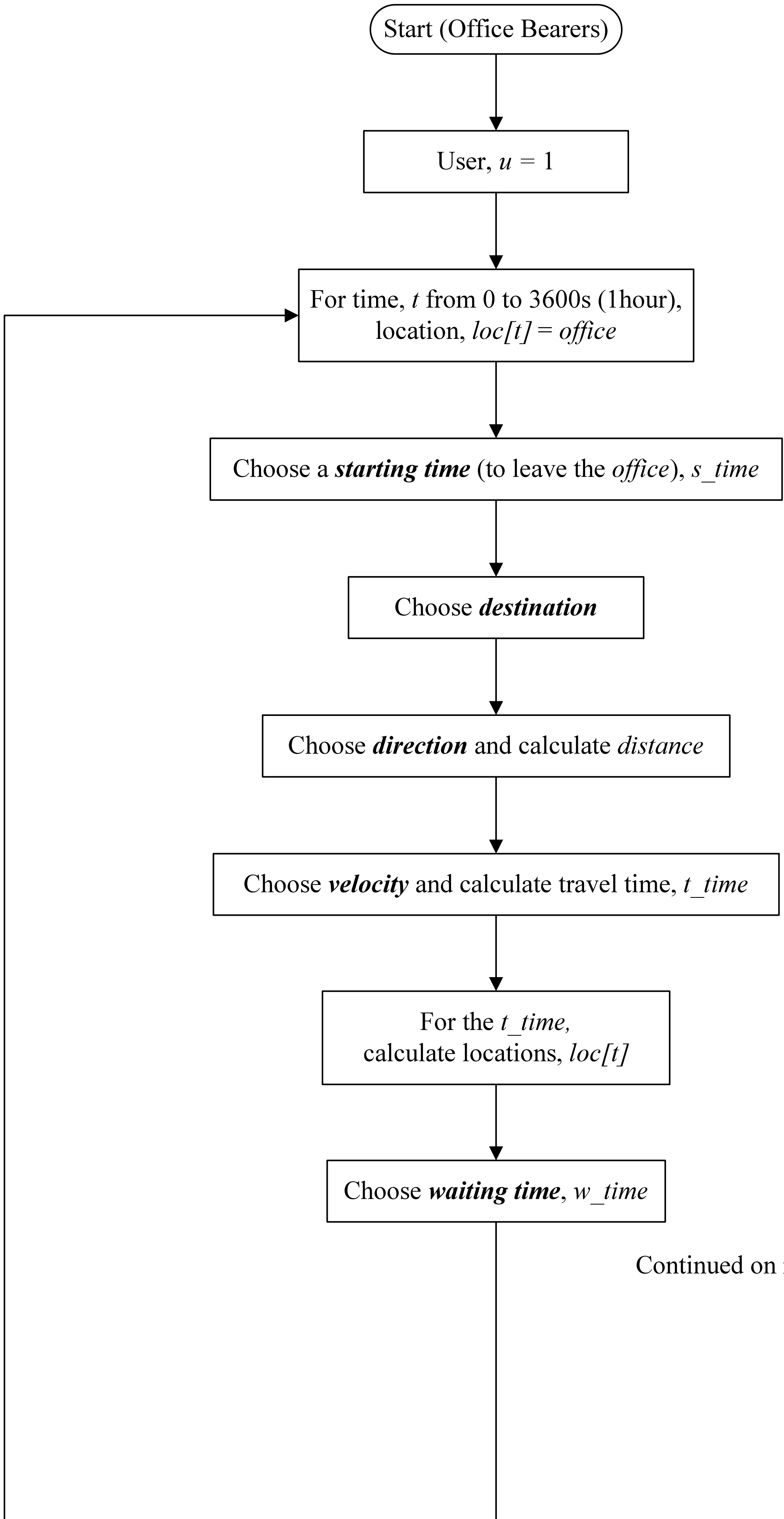
9.3.1 Case Study 2

The floor layout is the same as shown in Fig. 7.2. The problem definition is similar to that in Section 7.2.2. There are 24 potential base station sites (i.e. $N_{bs} = 24$). The CDMA Call Admission Control (CAC) strategy is used and the Grade of Service (GoS) adopted is 2%.

[5]The Signal-to-Interference Ratio (SIR) and the received and transmitted powers, discussed in Section 4.3.1 and shown in Fig. 4.4, are checked.

[6]As discussed in Section 3.2.2, during soft handover the user connects to the new base station before breaking the connection with the current base station.

[7]The performance is investigated by comparing the optimisation results obtained by using the *RCR* algorithm, described in Chapter 6.



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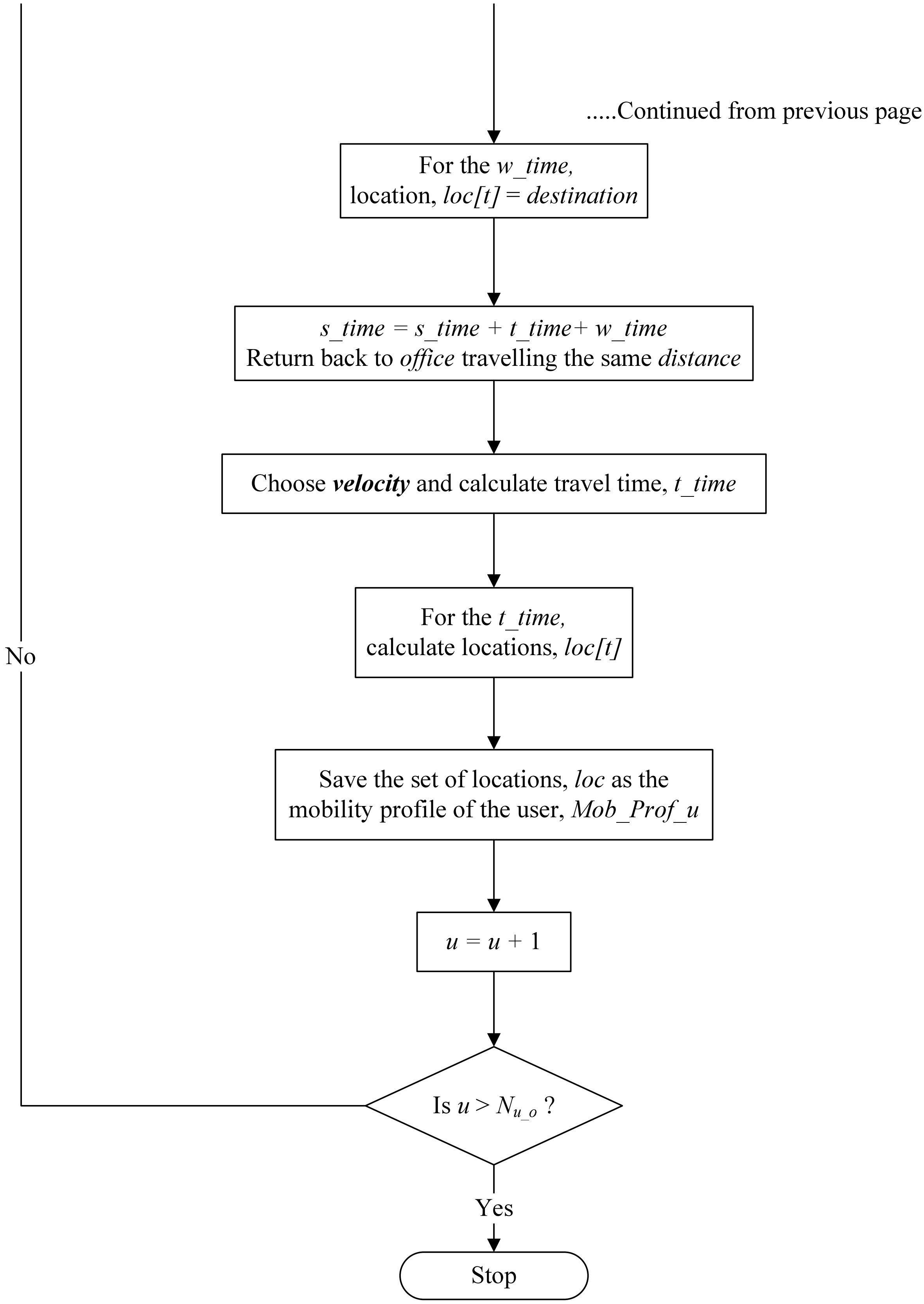
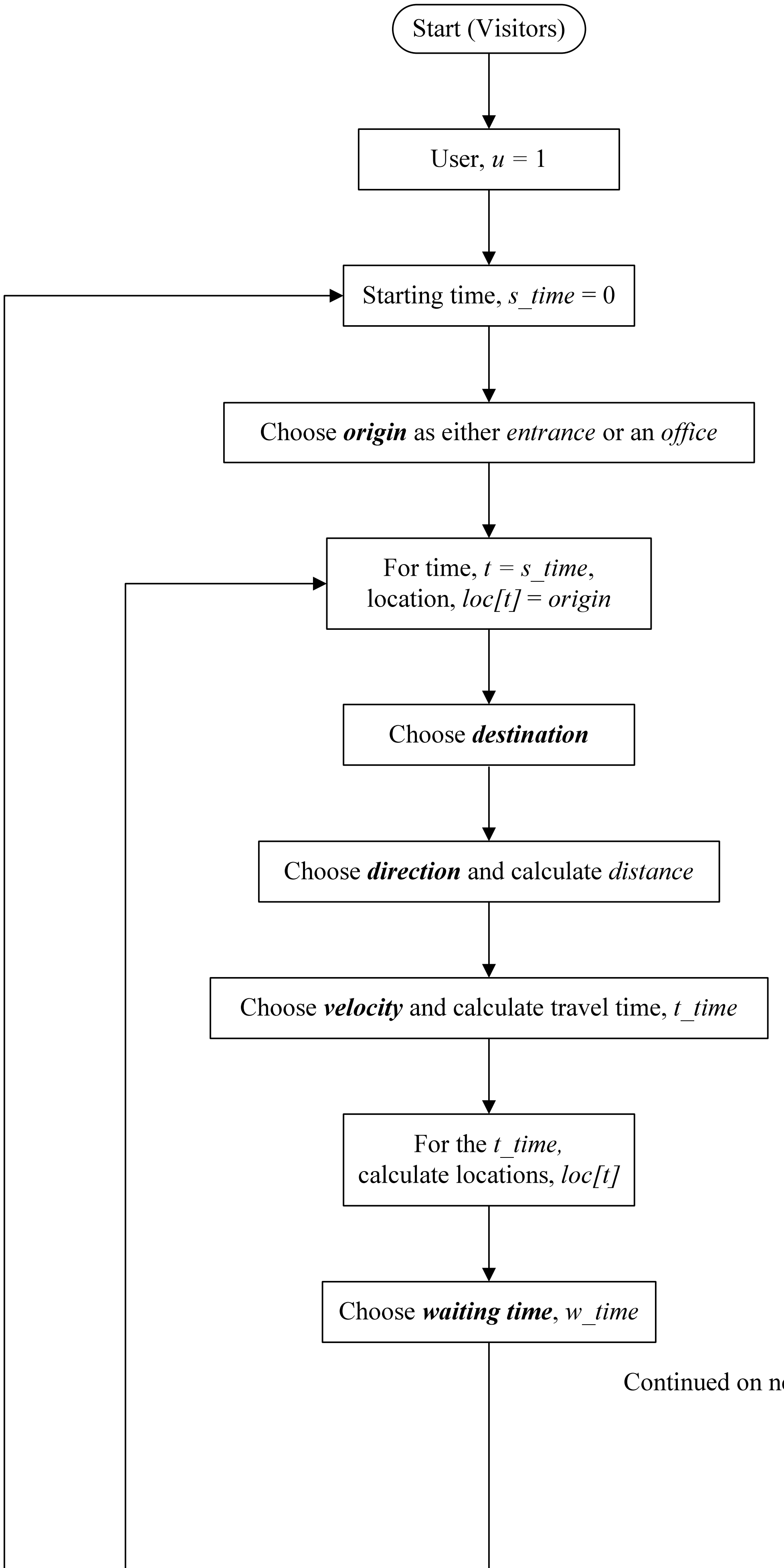


Figure 9.1: Generation of mobility profiles for office bearers.



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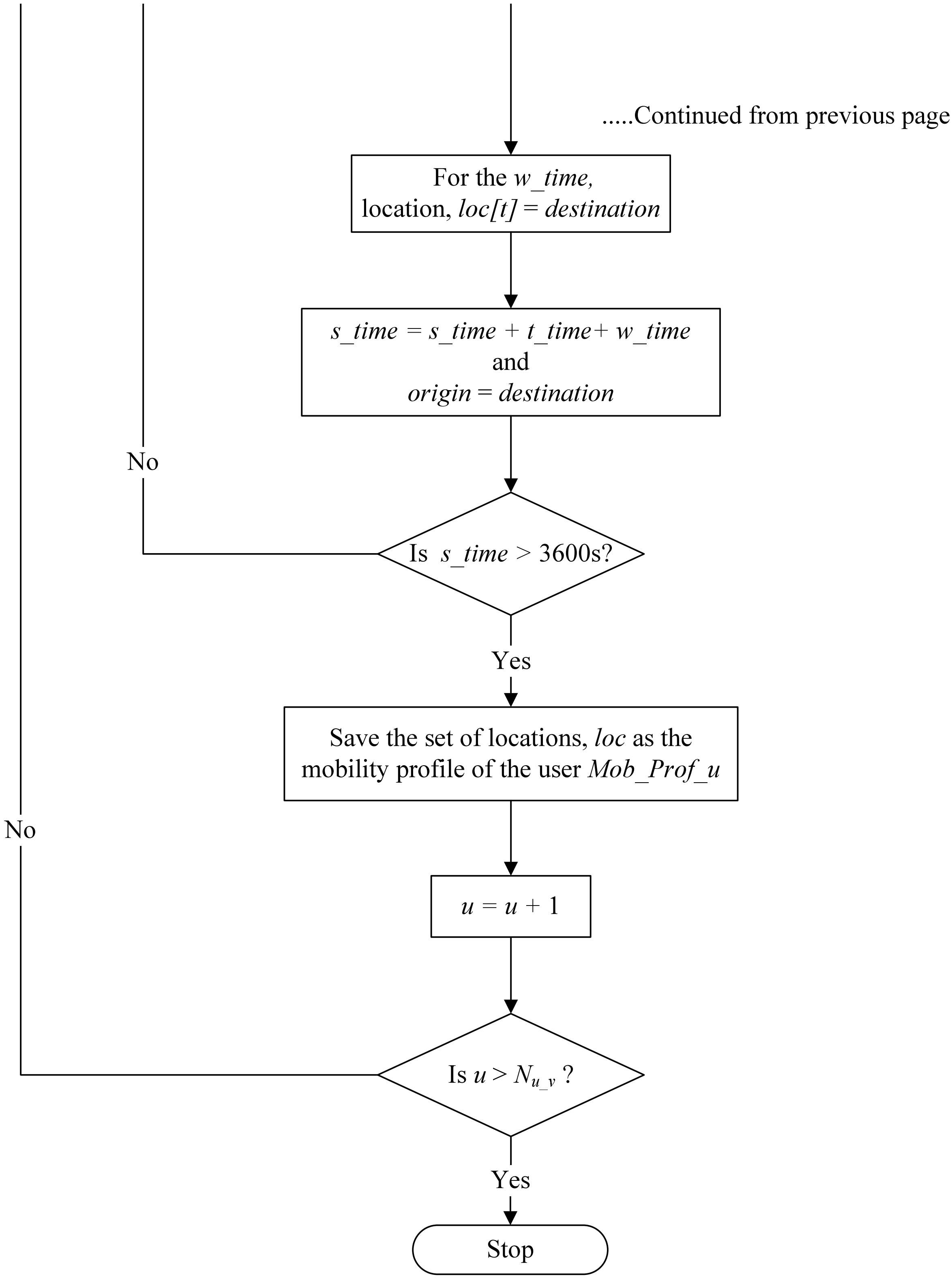


Figure 9.2: Generation of mobility profiles for visitors.

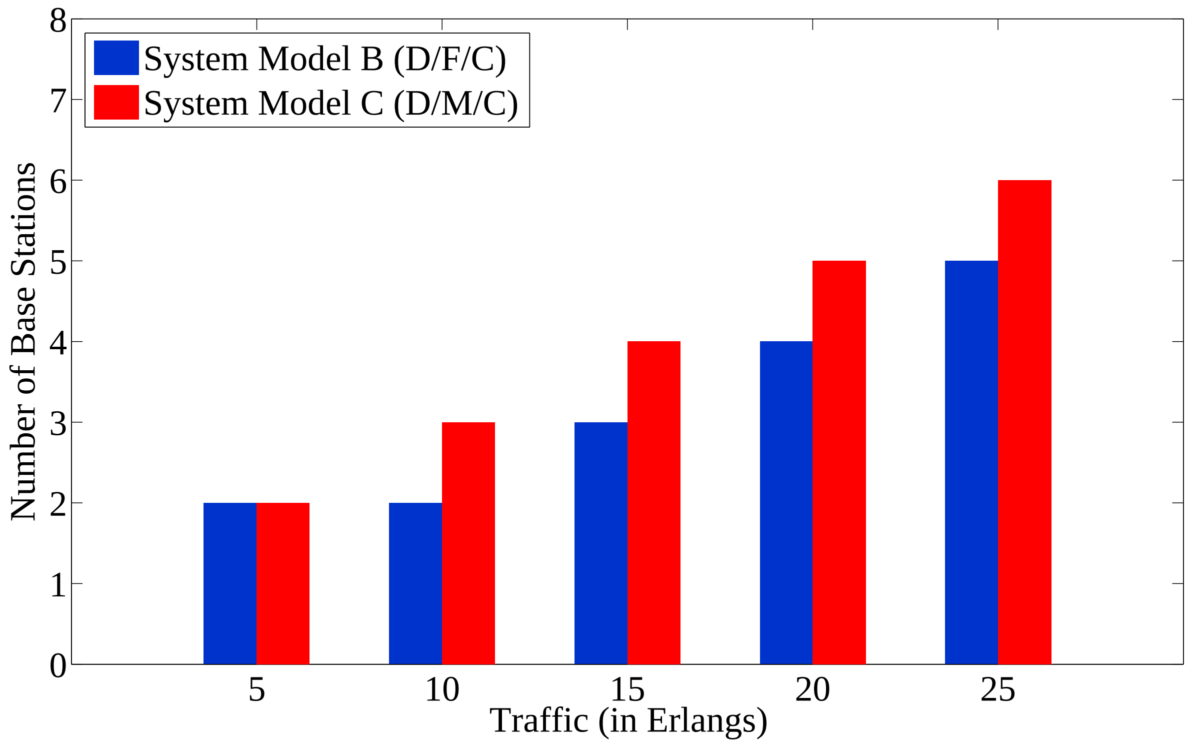


Figure 9.3: Optimisation results of System Models B (D/F/C) and C (D/M/C) for Case Study 2.

In the implementation of System Model B, there are 54 fixed user locations (i.e. $N_u = 54$) and the path loss values are found by in-building experimental measurements [5]. In the implementation of System Model C, there are 54 users (i.e. $N_u = 54$) which are divided into 24 office bearers[8] (i.e. $N_{u\_o} = 24$) and 30 visitors (i.e. $N_{u\_v} = 30$). The path loss values for System Model C are found by interpolating[9] the values used for the fixed user locations in System Model B.

System Models B (D/F/C) and C (D/M/C) are both implemented for five discrete scenarios[10] (corresponding to 5, 10, 15, 20 and 25 Erlangs of call traffic) to compare the number of base stations required to serve the users. Fig. 9.3 shows the optimisation results achieved by implementing System Models B and C. The results show that System Models B and C require the same number of base stations for the first scenario (5 Erlangs of traffic). As the traffic increases, more base stations are required for System Model C than System Model B. For example, as shown in Fig. 9.3, for the fourth scenario (20 Erlangs of traffic), System Model B requires 4 base stations whereas System Model C requires 5 base stations. This is because the users are

[8] The number of office bearers are chosen depending on the number of offices on the floor layout.

[9] The interpolation is performed using Matlab function 'TriScatteredInterp' which interpolates scattered data from a non uniform grid.

[10] Results for additional scenarios are shown in Appendix B.

fixed in System Model B and the Grade of Service (GoS)[11] depends only on the number of *new calls blocked*[12] (because they cannot connect to a base station). However, the users are moving in System Model C and the GoS depends on the number of *new calls blocked* (because they cannot connect to a base station) and *existing calls dropped* (because they cannot connect to another base station during handover). Thus, generally, more base stations are required for System Model C than System Model B to cope with the handover calls (in System Model C). Another case study (Case Study 3) is considered to check if similar results are achieved in a different environment.

9.3.2 Case Study 3

The Case Study 3 floor layout is shown in Fig. 7.4. The problem definition is similar to that in Section 7.2.3. There are 22 potential base station sites (i.e. $N_{bs} = 22$) and 80 users (i.e. $N_u = 80$) which are divided into 30 office bearers (i.e. $N_{u\_o} = 30$) and 50 visitors (i.e. $N_{u\_v} = 50$). The CDMA CAC strategy is used and the GoS adopted is 2%. In this Case Study also, the path loss values for System Models B and C are found by in-building experimental measurements and interpolation, respectively.

Fig. 9.4 shows the optimisation results achieved by implementing System Models B (D/F/C) and C (D/M/C). As shown in Fig. 9.4, System Models B and C are both implemented for five discrete scenarios. The results indicate that the number of base stations required for System Model C are generally more than System Model B. For example, as shown in Fig. 9.4, for the fourth scenario (20 Erlangs of traffic), System Model B requires 3 base stations whereas System Model C requires 4 base stations. Again, this is because in System Model B, GoS depends only on the number of *new calls blocked* whereas in System Model C, GoS depends on the number of *new calls blocked* and *existing calls dropped* (during handover).

In a real wireless communication system, the users can be fixed and/or moving. Thus, the optimal BSP should be able to cope with fixed as well as moving users. In Case Studies 2 and 3, System Model B (D/F/C) required fewer base stations than System Model C (D/M/C) and if System Model B is used to find the optimal BSP, the system will be under designed and will not be able to cope with the handover calls. Even though System Model B is easier to implement, it is not sufficient for finding the optimal BSP that will achieve the required GoS for a real system (with moving users). *Thus, mobility of users must be considered for finding the optimal BSP.*

As the aim of this chapter was to investigate the effect of user mobility on BSP, circuit switched calls were assumed for System Models B and C. In the next chapter, the effect of call

[11]GoS (described in Section 4.3.1) is the percentage of calls that are lost (new calls blocked and existing calls dropped) out of the total number of calls.

[12]The process of managing the calls i.e. Call Admission Control (CAC) Strategy was discussed in Section 4.3.1 and shown in Fig. 4.4.

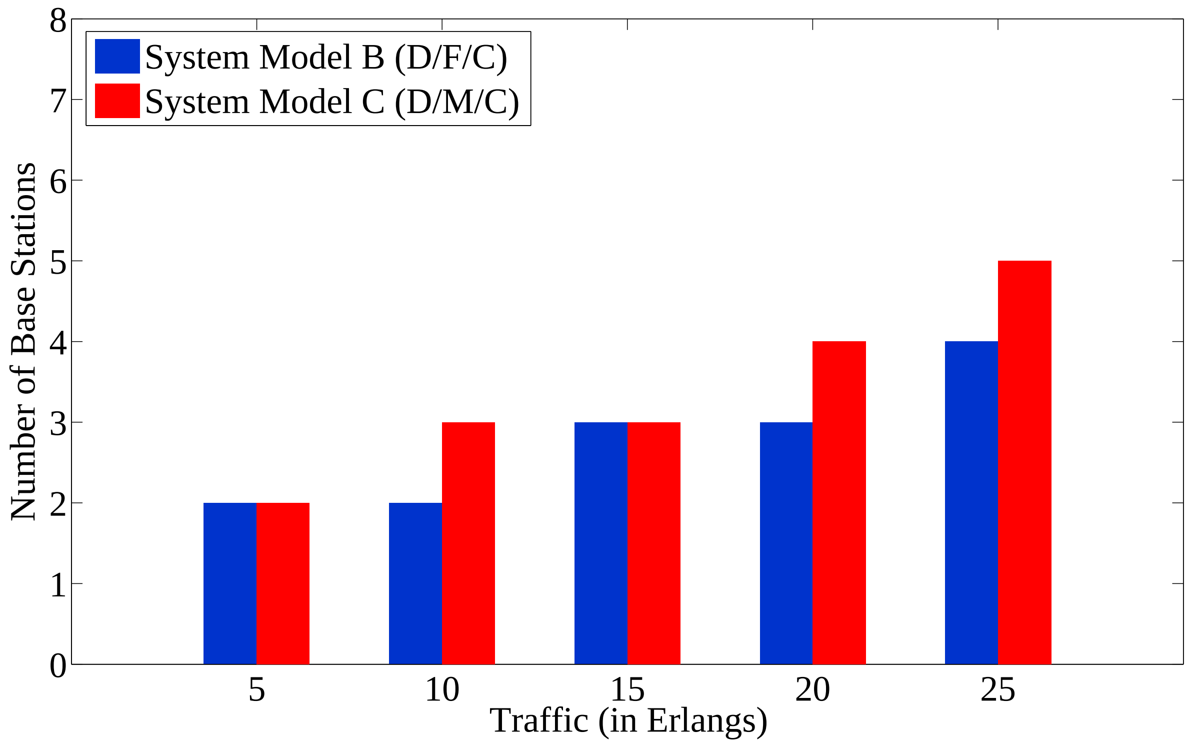


Figure 9.4: Optimisation results of System Models B (D/F/C) and C (D/M/C) for Case Study 3.

switching technologies on BSP is investigated using System Model C and a new system model, System Model D (D/M/P) with packet switched calls.

9.4 Summary

In this chapter, the effect of user mobility on BSP has been investigated. Two system models, System Models B (D/F/C) and C (D/M/C) are defined and implemented for the investigation. System Model B represents a system with dynamic call traffic, fixed users and circuit switched calls whereas System Model C represents a system with dynamic call traffic, moving users and circuit switched calls. The mobility of users, in System Model C, is assumed to follow the Random Waypoint model. The total number of users are divided into two categories — Office Bearers and Visitors and a mobility profile is generated for each user, depending on its category.

The effect of user mobility on the BSP problem is investigated by comparing the number of base stations required to serve the fixed users in System Model B and moving users in System Model C. Generally, more base stations are required by System Model C than System Model B. This is because, in System Model B, the GoS depends only on the number of new calls blocked whereas in System Model C, the GoS depends on the number of new calls blocked and existing calls dropped. In a real wireless communication system, the users can be fixed and/or moving.

BSP found considering only fixed users will not achieve the required GoS for moving users. Therefore, the mobility of users must be considered for finding the optimal BSP. In the next chapter, the effect of call switching technologies on BSP is investigated using System Models C (D/M/C) and D (D/M/P).

Chapter 10

Effect of Call Switching Technologies on Base Station Placement

10.1 Introduction

In Chapter 7, three factors (i.e. call traffic variability, user mobility and call switching technologies) affecting Base Station Placement (BSP) were discussed and the two options for each factor were described. Then, four system models[1], System Models A-D were proposed to investigate the effects of the three factors on the optimisation results of the BSP problem. In Chapters 8 and 9, the effects of call traffic variability and user mobility on BSP were investigated.

The aim of this chapter is to investigate the effect of call switching technologies on the BSP problem. The investigation is performed using System Models C (D/M/C) and D (D/M/P) which were proposed with different switching technologies. In Section 10.2, the implementations of System Models C and D are discussed to understand how circuit and packet switching technologies are modelled for indoor users. Then, in Section 10.3, optimisation results[2] for System Models C and D are compared to investigate the effect of call switching technologies on the BSP problem. The chapter is summarised in Section 10.4.

10.2 System Models for Call Switching Technologies

Table 10.1 shows the two system models (System Models C and D) proposed with different options of call switching technologies.

[1]The details of the System Models A-D are shown in Table 7.2.

[2]Optimisation results are obtained by applying System Models C and D to case studies.

System Model	Call Traffic (Static/Dynamic)	User Mobility (Fixed/Moving)	Call Switching Technology (Circuit/Packet)
System Model C (**D**/**M**/**C**)	Dynamic	Moving	Circuit
System Model D (**D**/**M**/**P**)	Dynamic	Moving	Packet

Table 10.1: System Models for investigating the effect of call switching technologies on BSP.

10.2.1 System Model C (D/M/C)

As shown in Table 10.1, System Model C (D/M/C) represents a system with dynamic call traffic, moving users and circuit switched calls. The details of System Model C are the same as discussed in Section 9.2.2 and are summarised in this section.

Dynamic Traffic

Call traffic is termed dynamic when the users have variations in call arrivals and departures over time [86, pp88-92]. It is assumed that call traffic follows an Erlang distribution, wherein the call arrival rates follow a Poisson distribution, the call duration rates follow a Negative Exponential distribution and the blocked calls are cleared [4, pp221-232] [11, p77] [87, p14]. In the implementation of System Model C, call schedules are generated for 501 different trials[3] to find an overall optimal BSP and each trial represents call arrivals and departures in one busy hour. The details of generation are discussed in Section 8.2.2 (and shown in Fig. 8.3).

Moving Users

The users have mobility i.e. they can physically move while receiving calls. In the implementation of System Model C, the user mobility is assumed to follow the Random Waypoint model [16, p43] [85, p229] [89, p53]. The total number of potential users (N_u) are divided into two categories — Office Bearers and Visitors. A mobility profile (i.e. a set of locations for every second during the busy hour) is generated for each user as discussed in Section 9.2.2 (and shown in Figs. 9.1 and 9.2).

[3]The first trial is used as a 'warm up' period to prepare the system. The results of the first trial are excluded from the call failure rate statistics.

Circuit Switched Systems

The user call is circuit switched i.e. the user establishes a dedicated connection to the base station for the duration of the call [18, p667] [19, p333]. Thus, in the implementation of System Model C, a user connects to a base station when a call arrives, remains connected to the base station during the call and disconnects only when the call departs.

10.2.2 System Model D (D/M/P)

As shown in Table 10.1, System Model D (D/M/P) represents a system with dynamic call traffic, moving users and packet switched calls.

Dynamic Traffic

The assumptions and call schedules for the dynamic call traffic in System Model D are identical to System Model C. Thus, it is assumed that call traffic follows an Erlang distribution [11, p77]. System Model D is also implemented by generating call schedules for 501 different trials, as discussed in Section 8.2.2 (and shown in Fig. 8.3).

Moving Users

The users are moving while they receive calls. The assumptions for user mobility in System Model D are identical to System Model C. Thus, the user mobility is assumed to follow the Random Waypoint model [16, p43]. The mobility profiles are generated for the users as discussed in Section 9.2.2.

Packet Switched Systems

The user call is packet switched i.e. the user transmits the data by breaking it into packets [19, pp335-337] [85, pp217-218]. The packets transmitted by the users can have random arrival times and variable sizes [94, p39]. In the implementation of System Model D, the packets are combined into new fixed sized packets which are sent (or offered) in 'frames' to the base stations. The number of fixed sized packets per frame (or the bit rate) offered to each base station can be either constant or variable.

Constant-Bit-Rate (CBR) traffic is modelled by generating a constant number of packets in every frame and is thus, equivalent to circuit-switched traffic. An example of CBR traffic is traditional cellular voice traffic [94, p40]. Fig. 10.1a shows the probability density function for the CBR traffic with a mean of 1 packet per frame.

Variable-Bit-Rate (VBR) traffic is modelled by generating variable number of packets per frame. There are several examples of VBR traffic including Voice over IP (VoIP), web browsing, audio and video broadcasting and email [94, p34]. In this thesis, three generic distributions are used to model the VBR traffic, namely

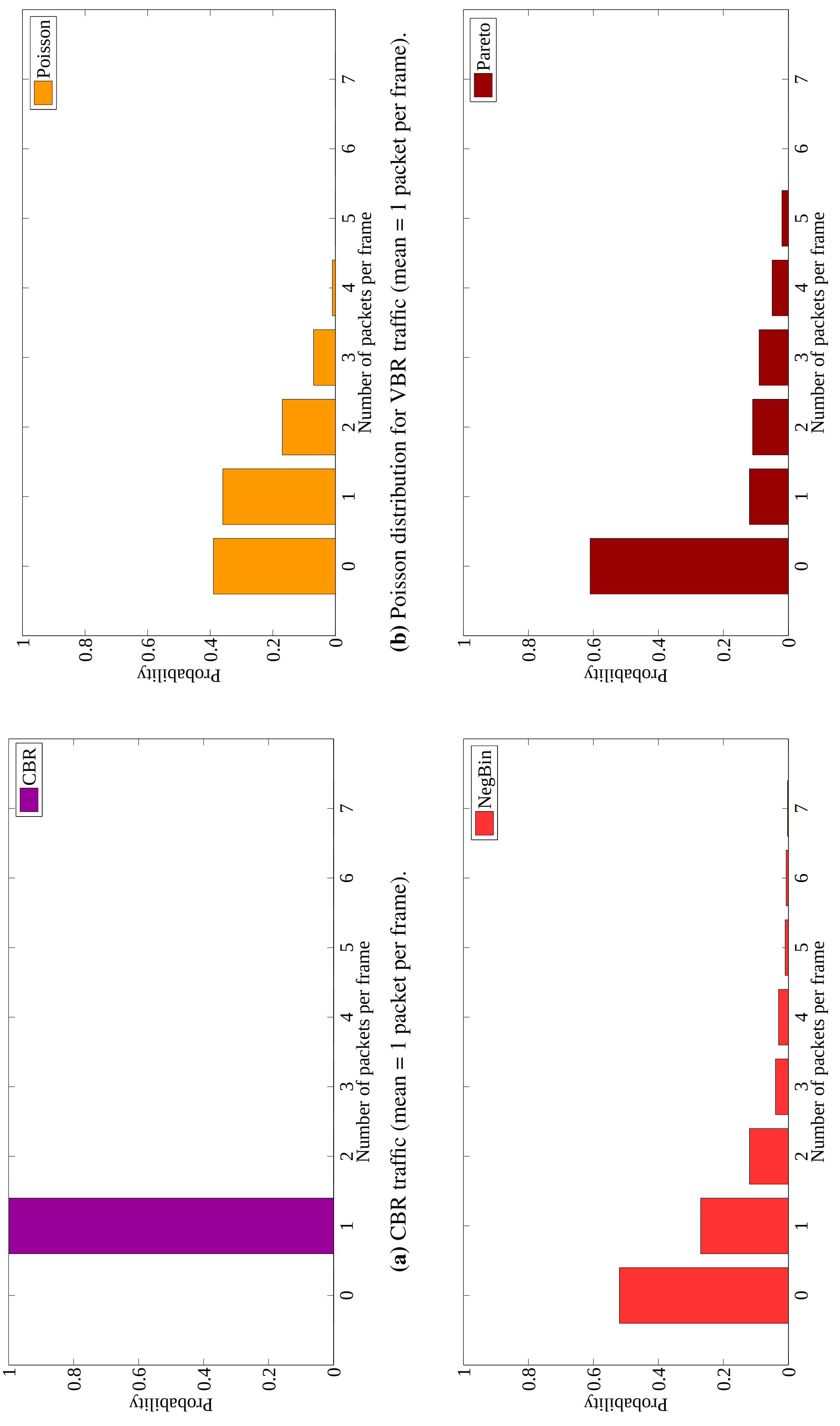
- Poisson distribution [94, p40] [95];
- Negative Binomial distribution [94, p41] [96]; and
- Pareto distribution [94, p43] [97].

Figs. 10.1b, 10.1c and 10.1d show the probability density functions for the three distributions with a mean of 1 packet per frame.

The (CBR or VBR) traffic **offered** (in frames) to the base stations is scheduled and then transmitted (or dropped) as shown (using an example) in Fig. 10.2. The **scheduling** of traffic depends on the maximum number of packets that can be sent in a frame which in turn depends on the number of spreading codes available. In Fig. 10.2, it is assumed that maximum 2 packets can be scheduled in a frame and thus, the packets of frame 2 and 5 are **queued** for scheduling in the next frame. During **transmission**, the queued packets are given priority and maximum 2 packets are transmitted in each frame. It is also assumed that the packets have a delay tolerance of 1 frame i.e. a packet can be delayed by no more than 1 frame. Therefore, in Fig. 10.2, a packet of frame 5 is **dropped** because it is not transmitted in frame 5 or 6 and cannot be delayed further.

Fig. 10.3 shows the flow diagram for the implementation of packet switching technology in System Model D. In each frame, the packets are **offered** to base stations depending on the number of users connected and the nature and distribution of traffic (CBR or VBR). Each connected user is assumed to offer a mean of 1 packet per frame to the base station [94, p52]. It is also assumed that 16 spreading codes are available on each base station for **scheduling**. Also, the queued packets (from the previous frame) are given priority for **transmission**. The delay tolerance of 1 frame is assumed and thus, the queued packets (from the previous frame) which are not transmitted (in the current frame), are **dropped**. The offered packets from the current frame which are not transmitted, are **queued** for scheduling in the next frame. The process of offering, scheduling, transmitting, dropping and queuing packets continues for 3600 frames. As there can be variations in the number of packets offered, all the users may not be transmitting at the same time.

System Models C and D both have dynamic traffic and moving users but the call switching technologies are different. System Model C represents a system with circuit switched calls and System Model D represents a system with packet switched calls and thus, the optimisation results of System Models C and D can be compared to investigate the effect of call switching



(a) CBR traffic (mean = 1 packet per frame).

(b) Poisson distribution for VBR traffic (mean = 1 packet per frame).

(c) Negative Binomial distribution for VBR traffic (mean = 1 packet per frame and variance = 2).

(d) Pareto distribution for VBR traffic (mean = 1 packet per frame and Hurst parameter = 0.8).

Figure 10.1: Probability density functions for CBR and VBR packet distributions.

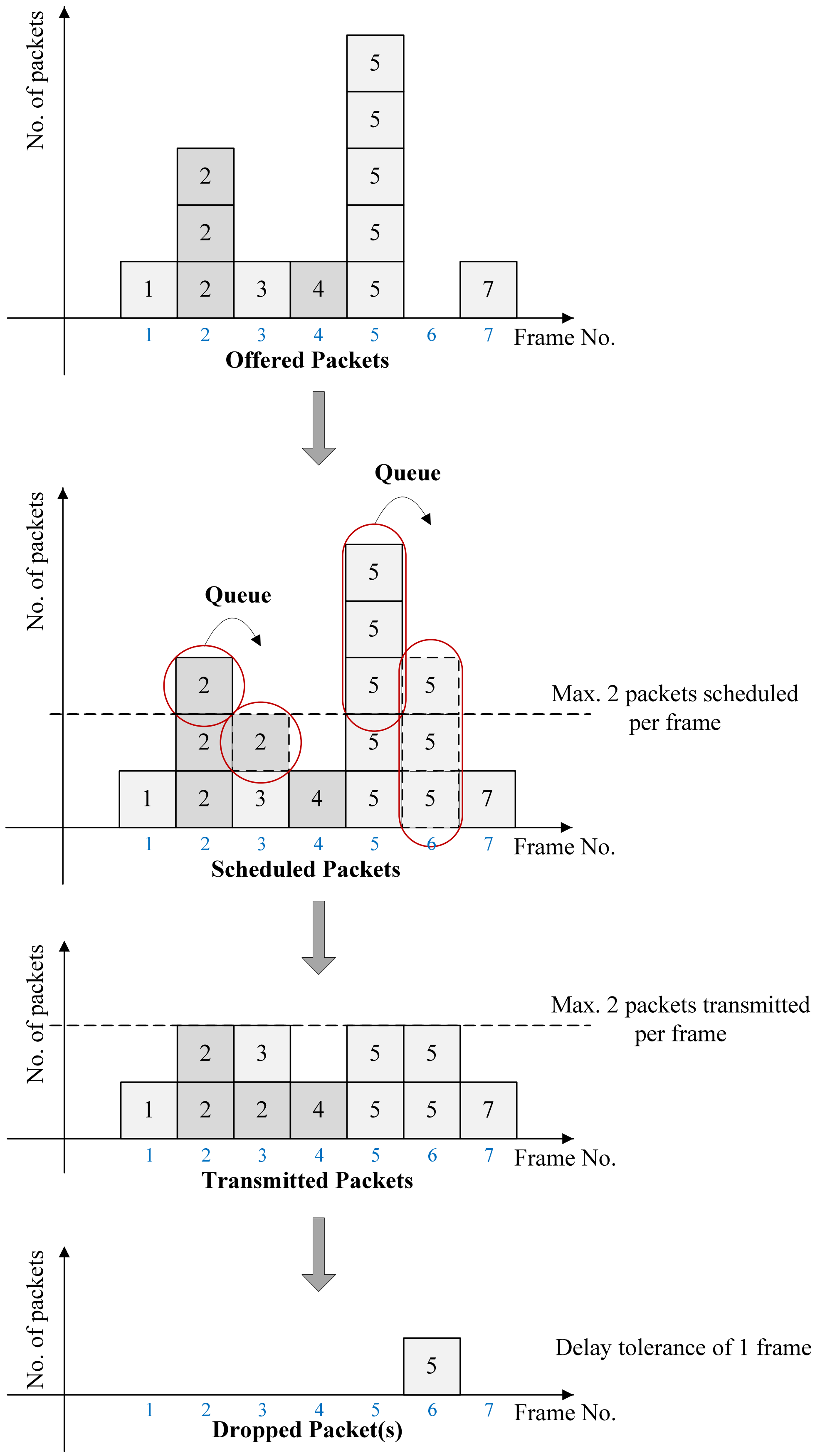


Figure 10.2: Packet scheduling and transmission process.

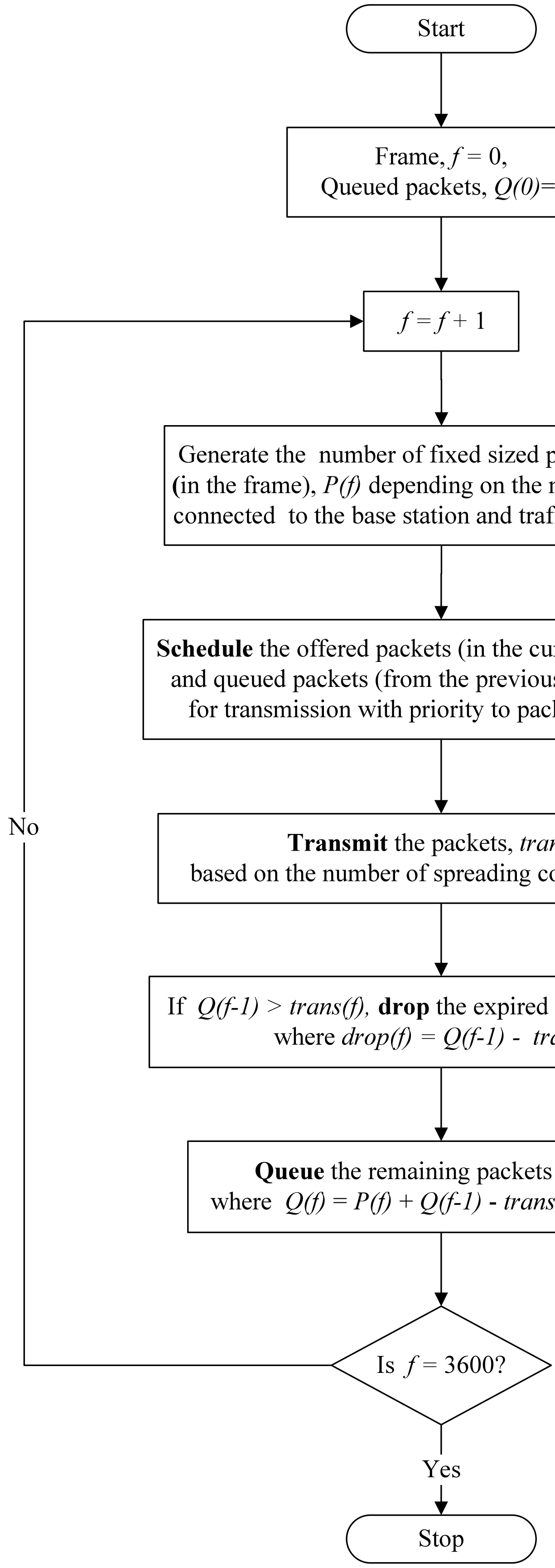


Figure 10.3: Implementation of packet switching technology.

technologies on the BSP problem. System Model C is easier and less time consuming to implement than System Model D because the packet traffic is not considered in System Model C. However, the aim is to investigate how the implementations of System Models C and D affect the optimisation results. Therefore, in the next section, two case studies have been considered to investigate the performance[4] of System Models C and D in different environments.

10.3 Effect of Call Switching Technology on Base Station Placement

Case Studies 2 and 3, described in Chapter 7 (Section 7.2), are used to investigate the effect of call switching technologies on the BSP problem by comparing the number of base stations required to serve the circuit switched calls in System Model C and packet switched calls in System Model D.

10.3.1 Case Study 2

The floor layout is the same as shown in Fig. 7.2 and the problem definition is identical to that in Section 9.3.1. System Models C (D/M/C) and D (D/M/P) are both implemented for five discrete scenarios[5] (corresponding to 5, 10, 15, 20 and 25 Erlangs of call traffic) to compare the number of base stations required to serve the users. Fig. 10.4 shows the optimisation results achieved by implementing System Models C and D (for CBR and VBR traffic). Three traffic distributions are assumed for VBR traffic — Poisson, Negative Binomial and Pareto. The results show that System Models C and D require the same number of base stations for the first two scenarios (5 and 10 Erlangs of traffic). Thus, the implementation of the two system models give the same optimisation results for small traffic scenarios.

As the traffic increases, System Model C and CBR traffic (in System Model D) generally require more base stations than VBR traffic (in System Model D). For example, as shown in Fig. 10.4, for the fourth scenario (20 Erlangs of traffic), System Model C and CBR traffic require 5 base stations whereas VBR traffic requires 4 base stations. As discussed in Section 10.2.2, CBR traffic (in System Model D) is equivalent to circuit switched traffic (in System Model C) and hence, the same number of base stations are required by both.

VBR traffic (Poisson, Negative Binomial and Pareto distributions) generally requires fewer base stations than CBR traffic because in VBR all the connected users are not transmitting at the same time, whereas in CBR all the connected users are transmitting at a constant rate. Thus,

[4]The performance is investigated by comparing the optimisation results obtained by using the *RCR* algorithm, described in Chapter 6.

[5]Results for additional scenarios are shown in Appendix B.

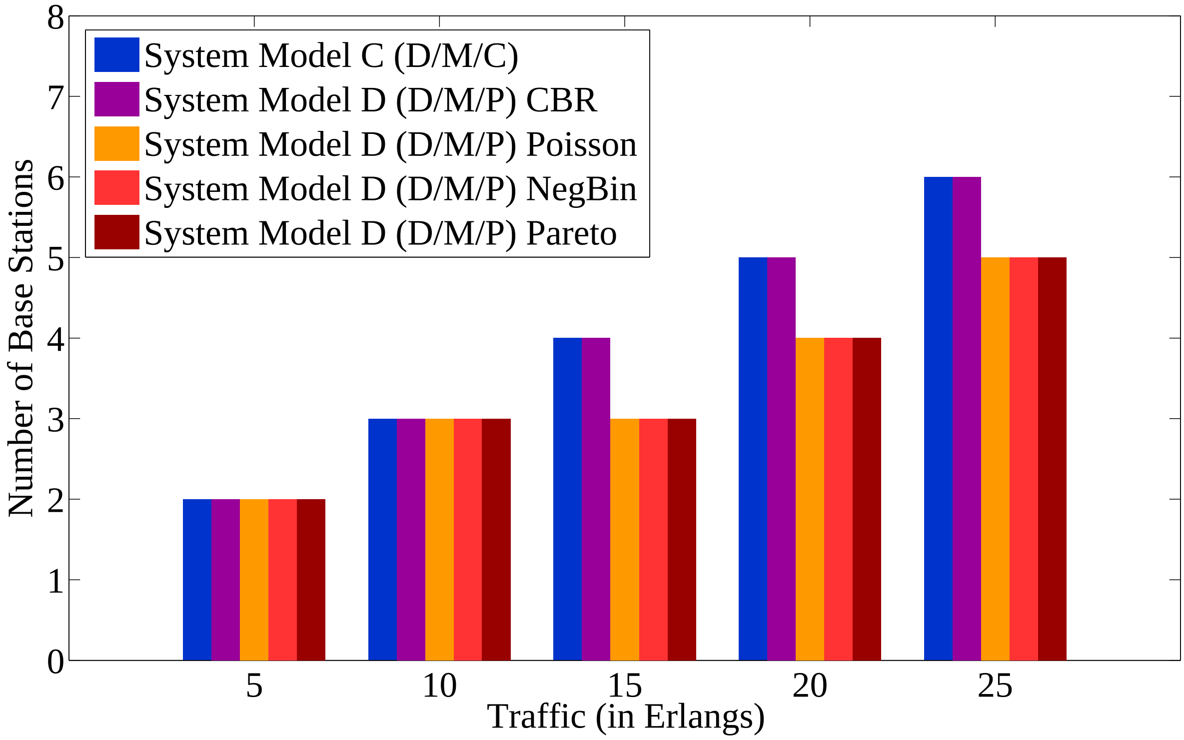


Figure 10.4: Optimisation results of System Models C (D/M/C) and D (D/M/P) for Case Study 2.

in VBR more users can connect to a base station than CBR. Also, in VBR, when there is bursty traffic (i.e. many packets offered), the non-transmitted packets are queued for transmission in the next frame and generally, not dropped. It is also observed that the number of base stations required is insensitive to the distribution of the VBR traffic.

Overall, System Model C (or CBR traffic (in System Model D)) is the *worst case* (i.e. requires more base stations) and thus, should be used for finding the optimal BSP to achieve the GoS for both switching technologies. This is also convenient as it simplifies the optimisation and detailed traffic models (and traffic distributions) do not need to be considered. Another case study (Case Study 3) is considered to check if similar results are achieved in a different environment.

10.3.2 Case Study 3

The Case Study 3 floor layout is shown in Fig. 7.4. The problem definition is identical to that in Section 9.3.2. Fig. 10.5 shows the optimisation results achieved by implementing System Models C (D/M/C) and D (D/M/P). As shown in Fig. 10.5, System Models C and D are both implemented for five discrete scenarios. The results indicate that the number of base stations required for System Model C and CBR traffic (in System Model D) are generally more than VBR traffic (in System Model D). For example, as shown in Fig. 10.5, for the fourth scenario (20

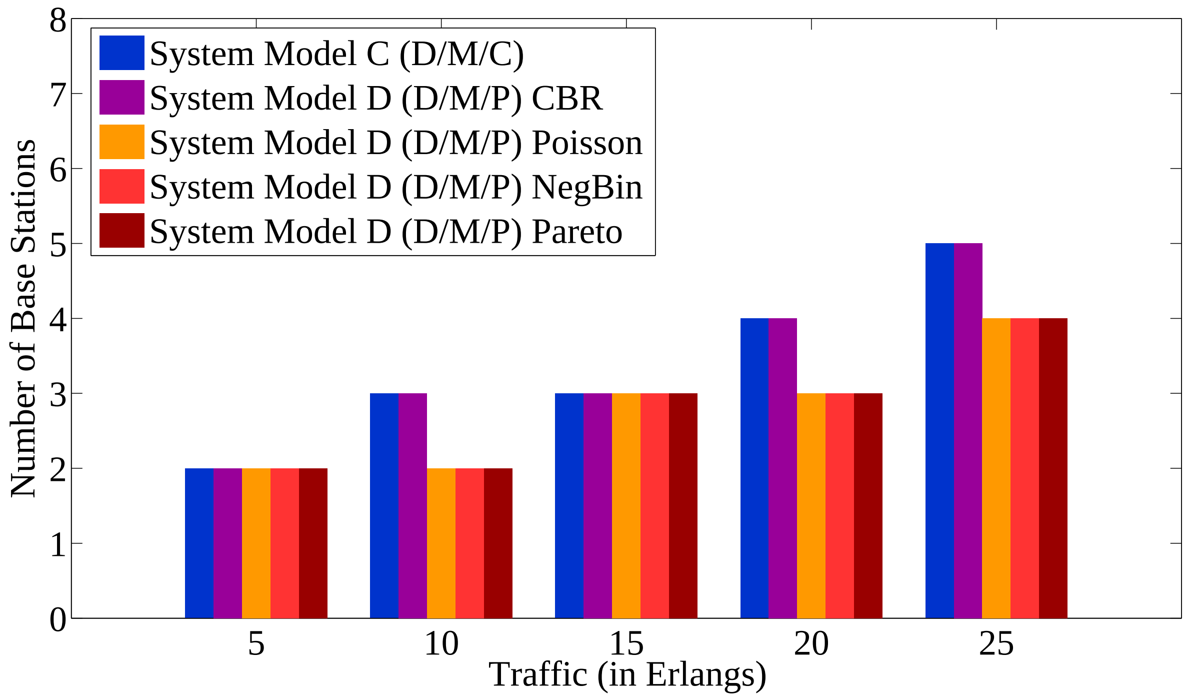


Figure 10.5: Optimisation results of System Models C (D/M/C) and D (D/M/P) for Case Study 3.

Erlangs of traffic), System Model C and CBR traffic require 4 base stations whereas VBR traffic requires 3 base stations. Again, this is because CBR traffic is equivalent to circuit switched traffic. Also, in VBR traffic, more users can connect to base stations than CBR traffic because all the connected users are not transmitting at the same time. Thus, System Model C can be used for finding the optimal BSP to achieve the GoS for both switching technologies. This also simplifies the optimisation as detailed packet traffic models do not need to be included in the implementation.

A real wireless communication system can have circuit and/or packet switched calls. Thus, the optimal BSP should be able to cope with traffic from both switching technologies. In Case Studies 2 and 3, VBR traffic (in System Model D (D/M/P)) generally required fewer base stations than System Model C (D/M/C) and if VBR traffic is used to find the optimal BSP, the system will be under designed and will not be able to cope with the circuit switched calls. On the other hand, Model C is not only easier to implement but can also find the optimal BSP to achieve the required GoS for both switching technologies. *Thus, circuit switched calls must be considered for finding the optimal BSP for systems with both switching technologies.*

Therefore, in the next chapter, System Model C is used to solve the BSP problem, which is extended to multi-floored buildings. Also, potential areas for future work are identified.

10.4 Summary

In this chapter, the effects of call switching technologies and different traffic distributions on BSP have been investigated. Two system models, System Models C (D/M/C) and D (D/M/P) are defined and implemented for the investigation. System Model C represents a system with dynamic call traffic, moving users and circuit switched calls whereas System Model D represents a system with dynamic call traffic, moving users and packet switched calls.

In System Model C, the user call is circuit switched i.e. the user establishes a dedicated connection to the base station for the duration of the call and in System Model D, the user call is packet switched i.e. the user transmits the data by breaking it into packets. The packets, offered to base stations in frames, can have either Constant-Bit-Rate (CBR) or Variable-Bit-Rate (VBR). CBR traffic is modelled by generating a constant number of packets per frame whereas VBR traffic is modelled by generating variable number of packets per frame (using three distributions, namely Poisson, Negative Binomial and Pareto).

The effect of call switching technologies on the BSP problem is investigated by comparing the number of base stations required to serve the circuit switched calls in System Model C and packet switched calls in System Model D. The number of base stations required by System Model C and CBR traffic (in System Model D) is the same and is generally more than the number of base stations required for VBR traffic (in System Model D). CBR is equivalent to circuit switched traffic (in System Model C) because all the connected users are transmitting at a constant rate. In VBR, more users can connect to a base station than CBR, because in VBR all the connected users are not transmitting at the same time. Also, in VBR, when there is bursty traffic, the non-transmitted packets are queued (with the intention of transmission in the next frame) and the number of base stations required is insensitive to the distribution of the VBR traffic.

A real wireless communication system can have circuit and/or packet switched calls. BSP found considering packet traffic will not achieve the required GoS for circuit switched traffic. Therefore, circuit switched calls must be considered for finding the optimal BSP (for systems with both switching technologies). This also simplifies the optimisation as detailed packet traffic models (and traffic distributions) do not need to be considered. In the next chapter, the BSP problem is extended to multi-floored buildings (and solved using System Model C) and potential areas for future work are identified.

Chapter 11

Optimisation of Multi-Floored Buildings and Future Work

11.1 Introduction

Case Studies 1-3 (defined in Chapters 5 and 7) were represented by single floor layouts (with potential base station sites and user locations on the same floor). In practice, indoor systems are generally multi-floored buildings, like office blocks and shopping malls. Therefore, in this chapter, the BSP problem is extended to multi-floored buildings (with potential base station sites and users on several floors).

The aim of the research reported in Chapters 8-10 was to investigate the effect of three factors (specifically call traffic variability, user mobility and call switching technologies) on Base Station Placement (BSP). It was concluded that dynamic call traffic, user mobility and circuit switched traffic must be considered in order to identify the optimal BSP. For this reason, System Model C (D/M/C), which includes dynamic call traffic, moving users and circuit switched calls, has been selected for the optimisation study reported in this chapter.

The aim of this chapter is to find the optimal number and locations of the base stations for multi-floored buildings. A real office block is analysed with users on two different floors inside the building and potential base station sites inside and outside the building. The optimisation is performed first by considering only *internal* base station sites and then, by considering both *internal* and *external* sites. Section 11.2 presents the physical layout of the building and the optimisation results. In Section 11.3, the potential areas for future work are identified. Section 11.4 presents a summary of the chapter.

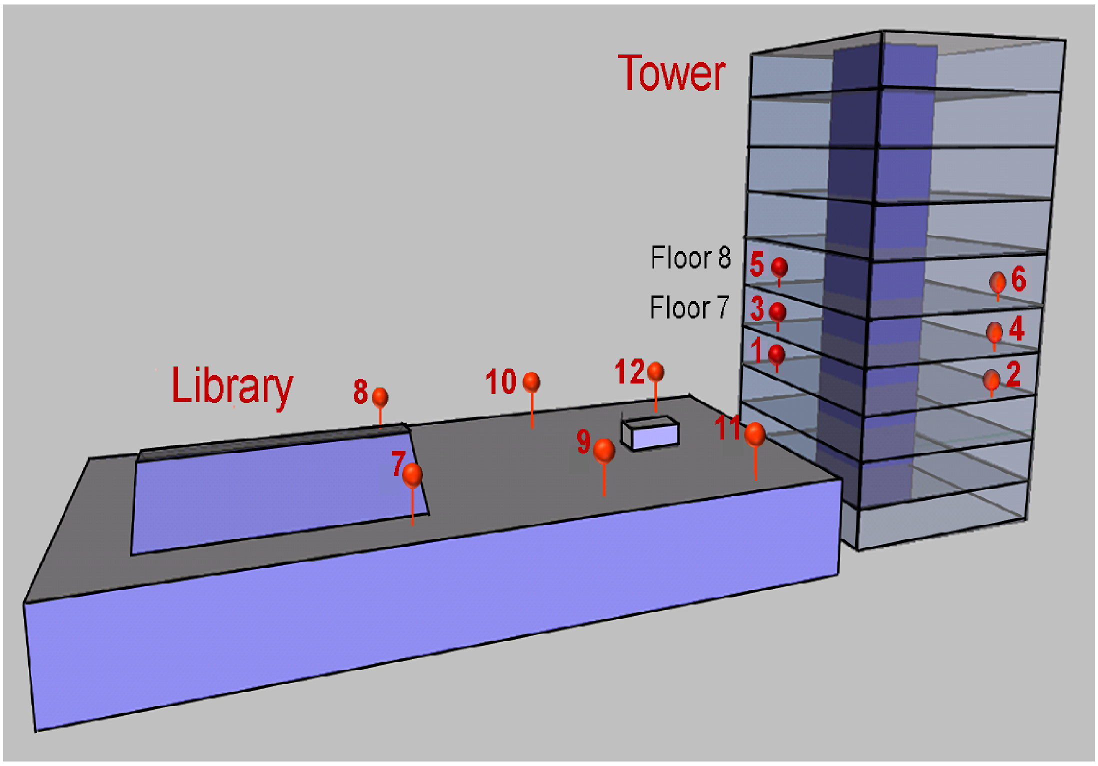


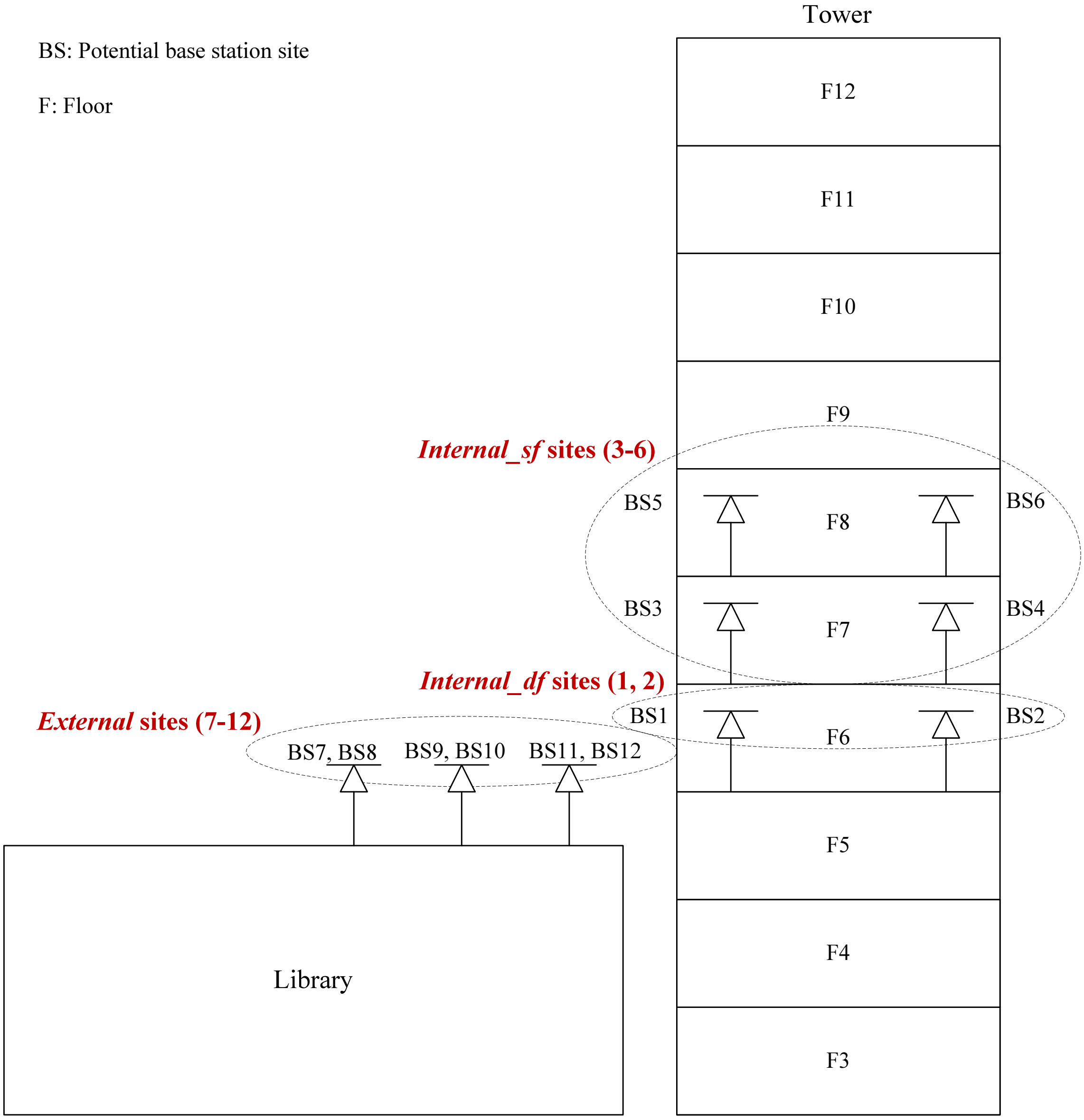
Figure 11.1: Three dimensional layout for Case Study 4.

11.2 Base Station Placement (BSP) in Multi-Floored Buildings

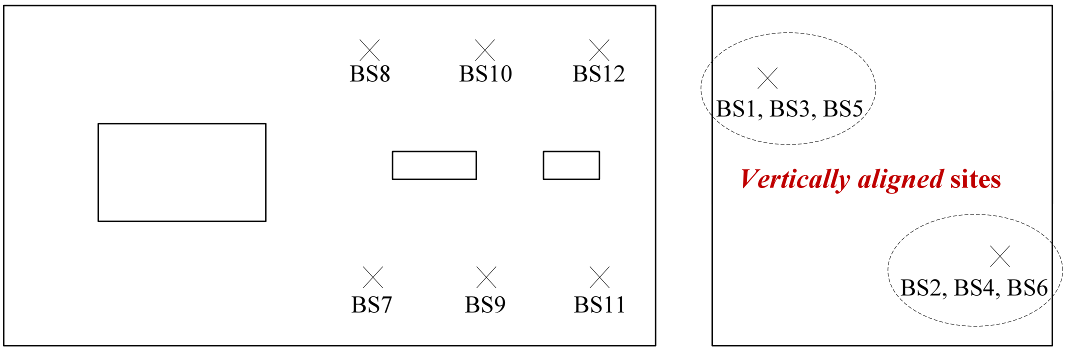
In this section, the indoor BSP problem is extended to multi-floored buildings, with potential base station sites located inside as well as outside the building. The optimal number and locations of base stations are found for different traffic scenarios for Case Study 4, shown in Fig. 11.1.

11.2.1 Physical Environment

Fig. 11.2 shows the elevation view and plan view of the building shown in Fig. 11.1. There are 12 potential base station sites and 108 potential users in the building. The users are assumed to be only on two floors of the building — Floor 7 (with 56 users) and Floor 8 (with 52 users). Table 11.1 describes the terminology used to classify the potential base station sites in Fig. 11.2.



(a) Elevation View.



(b) Plan View.

Figure 11.2: Layout of the potential base station sites for Case Study 4.

Terminology and Definition	Potential base station sites
External sites Potential base station sites outside the building.	(7, 8, 9, 10, 11, 12)
Internal sites Potential base station sites inside the building.	(1, 2, 3, 4, 5, 6)
Internal_sf sites *Internal* potential base station sites on the same floors (sf) as the users i.e. the sites on floors 7 and 8.	(3, 4, 5, 6)
Internal_df sites *Internal* potential base station sites on different floors (df) than the users i.e. the sites not on floors 7 and 8.	(1, 2)
Vertically aligned sites Potential base station sites in the same vertical line but on different floors inside the building.	(1, 3, 5) and (2, 4, 6)

Table 11.1: Terminology to classify the potential base station sites.

The path loss values are found by interpolating[1] the values found by in-building experimental measurements [24]. The CDMA Call Admission Control (CAC) strategy is used and the values of the CDMA parameters are the same as those used for Case Studies 1-3 (shown in Table 5.1). Again, the Grade of Service (GoS) adopted is 2%.

11.2.2 Results and Discussion

The optimisation is performed considering System Model C (D/M/C) which is described in Section 9.2.2 and has the following assumptions:

- The call traffic is dynamic and follows the Erlang distribution. The call schedules are generated for 501 different trials to find an overall optimal BSP;
- The users are moving and follow the Random Waypoint mobility model. The total number of users are divided into office bearers and visitors. A mobility profile is generated for each user assuming that the user can move on its assigned floor only; and
- The user call is circuit switched and the user establishes a dedicated connection to the base station for the duration of the call.

The optimisation is performed first by considering only *internal* (*internal_sf* and *internal_df*) potential base station sites and then, by considering both *internal* and *external* sites, for five discrete traffic scenarios (corresponding to 5, 10, 15, 20 and 25 Erlangs of traffic). The number of base stations required and the optimal BSP are found for each scenario.

Internal (internal_sf, internal_df) base station sites only

The 6 *internal* (4 *internal_sf* and 2 *internal_df*) potential base station sites are considered for optimisation. The results are shown in Table 11.2. If the call traffic is 5 Erlangs (Scenario I), two base stations are enough to serve the users and the optimal BSP is (3, 5) i.e. sites 3 and 5. The BSP suggested refers to one site on floor 7 and one on floor 8 (as shown in Fig. 11.2). These base stations are *vertically aligned*. This is consistent with the observation (in [98, 99]) that the call failure rate is minimum for *vertically aligned* base stations in a multi-floored building.

As the traffic increases, three base stations are required (Scenarios II and III) and the optimal BSP is (3, 4, 6). In these scenarios, one site is selected on floor 7 and one on floor 8 and the two sites are *vertically aligned*. The third site is another *internal_sf* base station site. In Scenarios IV and V, four base stations are needed to serve the users and all the *internal_sf* sites are selected (i.e. the optimal BSP is (3, 4, 5, 6)).

[1]The interpolation is performed using Matlab function 'TriScatteredInterp' which interpolates scattered data from a non uniform grid.

Scenario	Traffic (Erlangs)	No. of base stations required	Optimal BSP
I	5	2	(3, 5)
II	10	3	(3, 4, 6)
III	15	3	(3, 4, 6)
IV	20	4	(3, 4, 5, 6)
V	25	4	(3, 4, 5, 6)

Table 11.2: Optimal BSP with only internal base station sites.

Fig. 11.3 shows the percentage of calls connected to each site in the optimal BSP for the five scenarios. It is observed that when two base stations are required to serve the users (Scenario I), the call traffic is almost equally distributed over the two *vertically aligned* base station sites 3 and 5. When three base stations are required (Scenarios II and III), the two *vertically aligned* base stations (sites 4 and 6) each connect to a greater proportion of the calls compared to the third site (site 3). The percentage of the calls connected to each site does not vary significantly from Scenario II to III. As the traffic increases and four base stations are required (Scenarios IV and V), four *internal_sf* base stations are selected. In Scenarios IV and V, the *vertically aligned* base stations connect to a similar percentage of calls. The percentage of the calls connected to each site does not vary significantly from Scenario IV to V.

Internal and external base station sites

The 6 *internal* and 6 *external* potential base station sites are considered for optimisation. Table 11.3 shows the optimal results for the 12 potential base station sites. If the call traffic is 5 Erlangs (Scenario I) and two base stations are enough to serve the users, the optimal BSP is (3, 5). The results for Scenario I are the same as before (when there were only *internal* sites).

As the traffic increases, three base stations are required (Scenarios II and III) and the optimal BSP is (4, 6, 7). In these scenarios, one site is selected on floor 7 and and one on floor 8. The two selected sites are *vertically aligned*. The third site is an *external* site. Thus, if both *internal* and *external* potential base station sites are available, an *external* site is preferred over an *internal* site because it causes less interference to the other *internal* sites. In Scenarios IV and

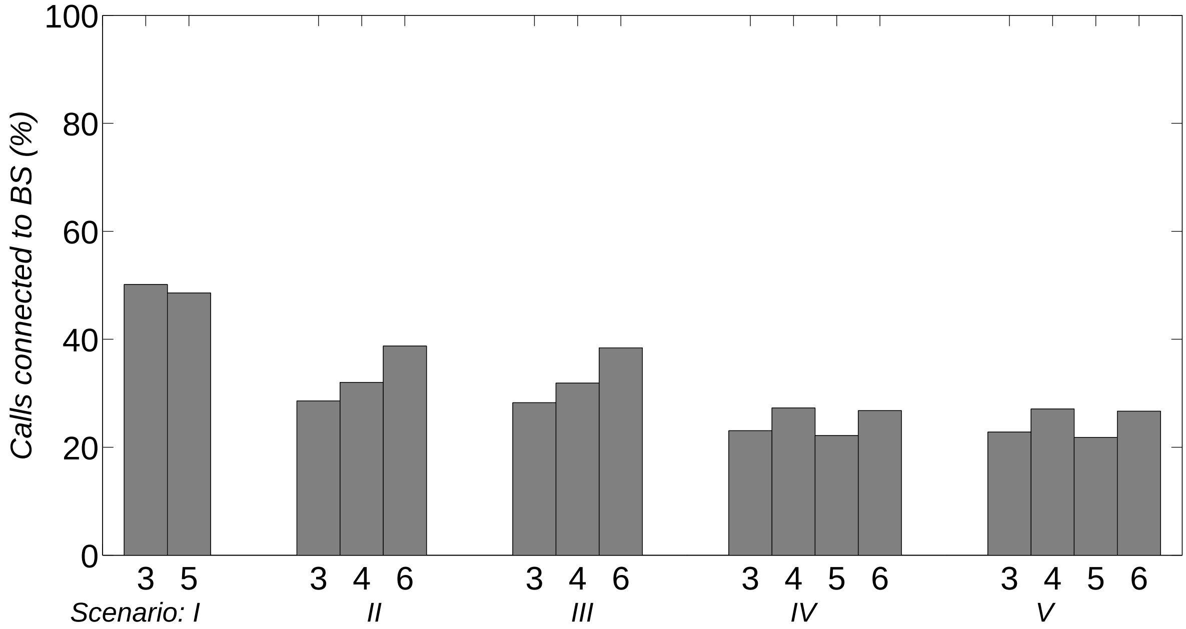


Figure 11.3: Percentage of calls connected to each base station with only internal base station sites.

Scenario	Traffic (Erlangs)	No. of base stations required	Optimal BSP
I	5	2	(3, 5)
II	10	3	(4, 6, 7)
III	15	3	(4, 6, 7)
IV	20	4	(4, 5, 6, 8)
V	25	4	(4, 5, 6, 8)

Table 11.3: Optimal BSP with internal and external base station sites.

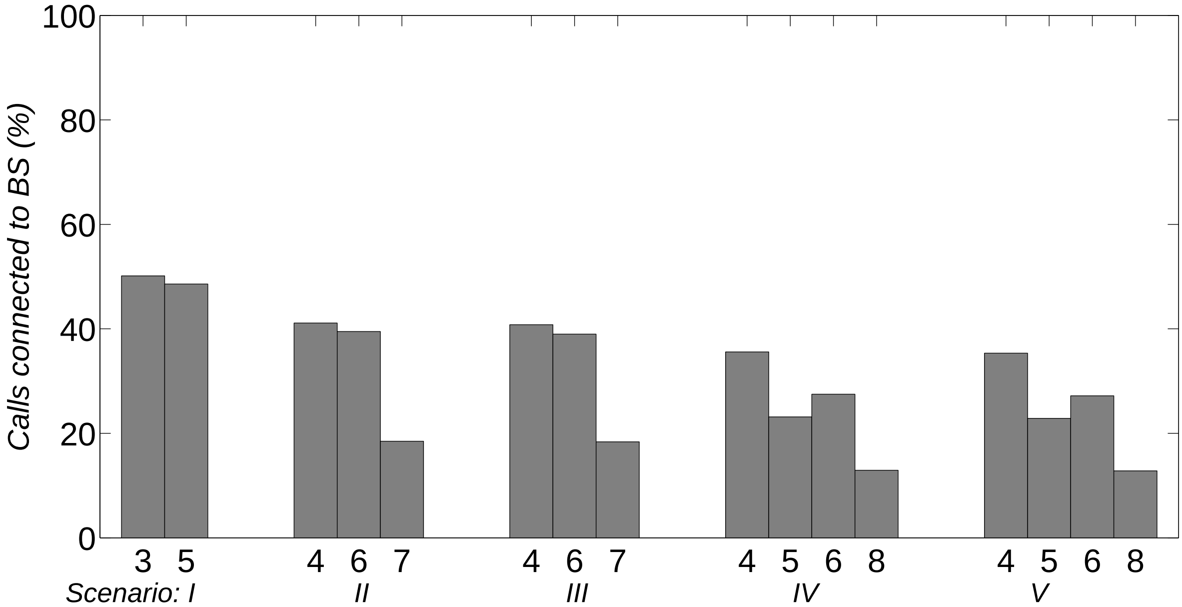


Figure 11.4: Percentage of calls connected to each base station with internal and external base station sites.

V, four base stations are needed to serve the users and the optimal BSP is (4, 5, 6, 8). When four optimal sites are required, three *internal_sf* sites and one *external* site are selected.

Fig. 11.4 shows the percentage of calls connected to each base station in the optimal BSP for the five scenarios. It is observed that when two base stations are required to serve the users (Scenario I), the call traffic is almost equally distributed over the two *vertically aligned* base station sites 3 and 5. When three base stations are required (Scenarios II and III), the two *internal_sf vertically aligned* sites (sites 4 and 6) each connect to the majority of the calls and a small percentage of calls is connected to the *external* site (site 7). The signal from the *external* site is weaker compared to an *internal* site and thus it connects to a small percentage of users. The percentage of the calls connected to each site does not vary significantly from Scenario II to III.

As the traffic increases and four base stations are required (Scenarios IV and V), three *internal_sf* sites (sites 4, 5 and 6) connect to the majority of the calls. The two *vertically aligned* sites (sites 4 and 6) each connect to a greater percentage of calls compared to the third site (site 5). The *external* site (site 8) connects to the least percentage of calls. The calls on floor 7 divide mainly between sites 4 and 8 with site 4 connecting to the majority of the calls. On floor 8, the calls are divided between sites 5 and 6 with site 6 (*vertically aligned* to site 4) connecting to a greater percentage of calls. The percentage of the calls connected to each site does not vary significantly from Scenario IV to V.

Therefore, for both the analyses, *vertically aligned internal_sf* base station sites produce the minimum call failure rate and connect to almost equal percentages of calls. As the traffic increases, an *external* site is selected over an *internal* site because it causes less interference to the other *internal* sites. When the traffic becomes high and more base stations are required, another *internal_sf* site is selected to cope with the load. The *internal* base station sites serve the greater proportion of calls with maximum calls being served by *vertically aligned internal* sites.

The propagation conditions within the building are typical of many office buildings [12, p46]. It is therefore expected that the results and trends observed here may be transportable to other buildings of similar construction. However, the degree of transportability to other indoor buildings needs to be examined in the future. Similarly, some other issues identified during the course of this research are recommended for future work in the next section.

11.3 Recommendations for Future Work

This thesis presents a comparison of the algorithms for optimisation and investigates the effect of various factors on BSP in indoor wireless communications systems. The results obtained from this research are likely to be useful for the deployment of wireless systems. However, there are several possible extensions to this research and it is now appropriate to discuss a selection of the possible future directions.

Priority calling

In this thesis, the CDMA CAC (discussed in Section 4.3.1) treats all the calls on a ‘first-come, first-serve’ basis i.e. admits a new call only if it does not interrupt any existing call. Thus, it is assumed that there is no ‘priority calling’ i.e. it does not give priority to any call and all users are competing equally for the available resources [100, p14] [101, p152]. However, it is possible that some calls are more important than others and thus, should be given a higher priority for connection [1, p12]. For example, calls to the fire department, police or hospital are urgent compared to administrative calls and must be connected even if it means interrupting existing, lower priority calls. The effect of including priority calling on BSP could be investigated as an interesting extension to the work presented.

Delay of blocked calls

The blocked calls can be handled in two ways — ‘blocked calls *cleared*’ and ‘blocked calls *delayed*’ [17, pp78-80] [18, p362]. In the implementation of dynamic traffic (in Section 8.2.2), it is assumed that the blocked calls are *cleared* from the system i.e. if a call cannot connect to a base station, it is lost. This assumption is used in the Erlang B system [88, pp96-99]. However, in the Erlang C system, the blocked calls are *delayed* by putting them in a queue. For example, systems with the call attendant service play a recorded message in the background, like " your call is important to us.....", until the call is connected. It will be worthwhile to examine how the implementation of the Erlang C system affects the BSP problem.

Three-dimensional mobility

In Section 11.2, the BSP problem is extended to multi-floored buildings by considering a real office building. The optimisation is performed considering dynamic call traffic and moving users. However, the mobility of the users is limited to two dimensions i.e. it is assumed that a user can move on his/her assigned floor only. In indoor environments, three-dimensional mobility is possible as the users can also have vertical motion through elevators and stairs [90, 91, 102]. Thus, the mobility model used for optimisation should include horizontal motion (bounded by outer walls) as well as vertical motion (though elevators and stairs). The extension of the BSP mobility model to three dimensions would be a valuable future development.

Optimisation of OFDMA Systems

Orthogonal frequency division multiple access (OFDMA) is popular and is being used in many wireless systems including WiFi and WiMAX [103, pp2-6]. In an OFDMA system, a base station assigns subsets of its subcarriers to the users [103, p105] [104, pp10-13]. The number of subcarriers assigned depend on several factors including the required data rate and the desired probability of bit error.

In this thesis, the CDMA CAC strategy is used. This is because the interference models for CDMA systems are well developed and widely used for radio planning whereas the interference models for OFDMA systems are still being developed [25–27]. The deployment of base stations for OFDMA systems will be an interesting area for future study. The application of the optimisation algorithms for solving the BSP problem (for OFDMA systems) and investigating the factors affecting BSP is recommended as an extension to this research.

11.4 Summary

In this chapter, the problem of BSP in multi-floored buildings has been investigated. A real office building is considered (as an example) with users on two different floors (inside the building) and potential base station sites inside and outside the building. The optimisation is performed first by considering only *internal* base station sites and then, by considering both *internal* and *external* sites.

It is observed that for both the analyses, *vertically aligned internal_sf* base station sites produce the minimum call failure rate and almost equal percentages of calls connect to these base stations. As the traffic increases, another *internal_sf* site is selected in the first analysis but an *external* site is selected to serve a small proportion of users in the second analysis. Thus if both *internal* and *external* potential base station sites are available, an *external* site is selected over an *internal* site because it causes less interference to the other *internal* sites. When the traffic becomes high and more base stations are required, another *internal_sf* site is selected to cope with the traffic. The *internal* base station sites serve the greater proportion of calls with maximum calls being served by *vertically aligned internal* sites. The percentage of the calls connected to the sites does not vary significantly with traffic if a constant number of base stations is required to serve the users.

The recommendations for future work, discussed in this chapter, include priority calling, delay of blocked calls (by queuing), three-dimensional mobility and optimisation of OFDMA systems.

Chapter 12

Conclusions

The developments in wireless communication systems have enabled pervasive access to voice and data communication services [1, p3] [2, p1]. Along with the extensive use of outdoor wireless systems, the demand for indoor wireless systems, such as within high-rise office buildings and shopping malls, has been increasing rapidly [3, p1] [4, pp71-72]. Engineers responsible for deploying wireless systems are concerned with maximising the quality and capacity of the system while minimising the interference and cost [5, p3]. In addition, indoor wireless systems must cope with three-dimensional variations in signal strength and limitations in site selection. Consequently, the indoor Base Station Placement (BSP) problem is a multi-objective, multi-dimensional optimisation problem with many opposing constraints.

This thesis provides a practical and useful framework for solving the indoor BSP problem for CDMA systems, using mathematical models and optimisation algorithms and considering the effect of several factors on BSP.

In this thesis, the aim of BSP optimisation has been to find the minimum number and locations of base stations to serve the given set of users in an indoor environment using the defined Call Admission Control (CAC) strategy and achieving the desired Grade of Service (GoS). The BSP problem is quantified by modelling the quantification components (i.e. decision variables, constraints and objective function). The decision variables correspond to whether a base station is to be deployed at a potential base station site and whether a link is to be established from this potential site to a user. The constraints are modelled based on the CDMA CAC strategy and the required GoS. The objective of the optimisation is to minimise the number of base stations required to serve the given set of users ensuring all the constraints are met.

Four (previously) existing algorithms (Brute Force Search (*BFS*), Genetic Algorithm (*GEN*), Greedy Algorithm (*GRE*) and Ngadiman's Algorithm (*NGA*)) for solving the BSP problem have been implemented and compared. The (previously) existing algorithms are seen to provide an almost mutually exclusive tradeoff between accuracy and efficiency. In particular, *BFS* and *GEN* are found to be accurate but not very efficient whereas *GRE* and *NGA* are efficient but not accurate.

The (previously) existing algorithms have been used to develop a new hybrid algorithm (***RCR***) for solving the BSP problem for indoor wireless communication systems. In this algorithm, ***R**eduction Estimation* estimates the minimum number of base stations required to serve a given set of users, and ***C**ombinatorial Optimisation* (either alone or in conjunction with ***R**eduction Approximation*) identifies the optimal BSP combination for the given set of users. *RCR* is found to be as accurate as *BFS* and more accurate than *GEN*, *NGA* and *GRE*. The computational time of *RCR* is higher than *GRE* and *NGA* but remains feasible for practical applications. Thus, *RCR* is seen to identify optimal deployments, without significantly compromising accuracy and efficiency.

RCR has been used to investigate the effects of three factors, namely call traffic variability, user mobility and call switching technologies on the BSP problem. In this thesis, two options are considered for each factor — call traffic can be static or dynamic, users can be fixed or moving and call switching technology can be circuit or packet switched. Four system models, System Model A (S/F/C), System Model B (D/F/C), System Model C (D/M/C) and System Model D (D/M/P) are proposed with different combinations of the options.

System Models A (with static traffic) and B (with dynamic traffic) have been used to investigate the effect of call traffic variability on the BSP problem. It is seen that even though static call traffic model is easier to implement, it is not sufficient for finding the optimal BSP that will achieve the required GoS for systems which have variations in call arrivals and departures. This is because there are a fixed number of active users in static traffic but variable number of calls in dynamic traffic. Therefore, it is concluded that dynamic call traffic must be considered for finding the optimal BSP.

System Models B (with fixed users) and C (with moving users) have been used to investigate the effect of user mobility on the BSP problem. It is seen that even though fixed user system model is easier to implement, it is not sufficient for finding the optimal BSP that will achieve the required GoS for systems which can have fixed and/or moving users. This is because when the users are fixed, GoS depends only on the number of new calls blocked whereas when the users are moving, GoS depends on the number of new calls blocked and existing calls dropped (during handover). Thus, it is concluded that user mobility must be considered for finding the optimal BSP.

System Models C (with circuit switched calls) and D (with CBR and VBR packet switched calls) have been used to investigate the effect of call switching technologies on the BSP problem.

It is seen that circuit switched call traffic model is not only easier to implement but can also find the optimal BSP to achieve the required GoS for systems which can have circuit and/or packet switched calls. The CBR traffic is seen to be equivalent to circuit switched traffic as all the connected users are transmitting at a constant rate. In VBR traffic, more users can connect to a base station because all the connected users are not transmitting at the same time and when there is bursty traffic, the non-transmitted packets are queued. Thus, the conclusion is that circuit switched call traffic must be considered when finding the optimal BSP for systems with both switching technologies.

The BSP problem has been extended to multi-floored buildings (with *internal* and *external* base station sites) and solved using System Model C (D/M/C). It is seen that *vertically aligned internal_sf* base station sites are always included in the optimal BSP (as they produce the minimum call failure rate) and connect to almost equal percentages of calls. As the traffic increases, an *external* site is selected over an *internal* site because it causes less interference to the other *internal* sites. The *internal* base station sites serve the greater proportion of calls with maximum calls being served by *vertically aligned internal* sites.

Therefore, the key conclusions of this thesis are:

- The hybrid algorithm, *RCR* (developed using the previously existing algorithms) is an appropriate algorithm for optimisation of BSP in indoor wireless communication systems.
- The system model for BSP of indoor wireless communication systems must include
  - dynamic call traffic;
  - moving users; and
  - circuit switched calls.
- The optimal BSP for multi-floored buildings must include vertically aligned internal base station sites as they achieve the least call failure rate.

This thesis investigated the BSP problem of indoor wireless communication systems and the results obtained are intended to provide a useful and practical framework which can be extended to cater for the developments of new technologies and demands in the future.

Appendix A

Measurement Campaigns

This appendix describes how the in-building experimental measurement campaigns were performed in [5, 24] to measure the path loss values used in Chapters 7-11 of this thesis.

The measurement system was designed and built at The University of Auckland [5, pp183-189] [24, pp259-265]. As shown in Fig. A.1, the system consisted of twelve narrowband continuous wave transmitters, a Rhode and Schwartz ESVN40 test receiver and a laptop computer [5, pp185] [24, pp262].

The twelve narrowband transmitters transmitted at 500kHz frequency separation between 1800MHz and 1805.5MHz [5, pp184-185]. Each transmitter used a discone antenna which was optimised for frequencies in the region of 1800MHz. The transmitted signal was received by the test receiver which used a half wave dipole antenna [24, pp261]. The receiver was capable of rapidly scanning and sampling multiple frequencies and thus, all twelve signals could be measured pseudo simultaneously [5, pp184] [24, pp261]. The test receiver was connected to a laptop computer which recorded and processed the measurements using MS Excel. The details of the transmitters, receiver and antennas are described in [5, pp184-185] and [24, pp262-265].

In order to find the average path loss, the measurements were performed with a number of transmitters and receivers considering small areas of 1m diameter [5, pp189]. The antennas of the transmitters were positioned at a height of 2m above the floor level [5, pp189]. The received signal strength was recorded for 500 samples over each small area [5, pp189]. Then, the samples were averaged to find the local area mean[1] signal strength and the average path loss values between the transmitter and the receiver.

[1]The local area mean is the mean received signal averaged over a sufficient distance so that the short-term variations (due to fading) are eliminated, but medium-term variations (due to shadowing) and long-term variations (due to distance-dependence) are represented.

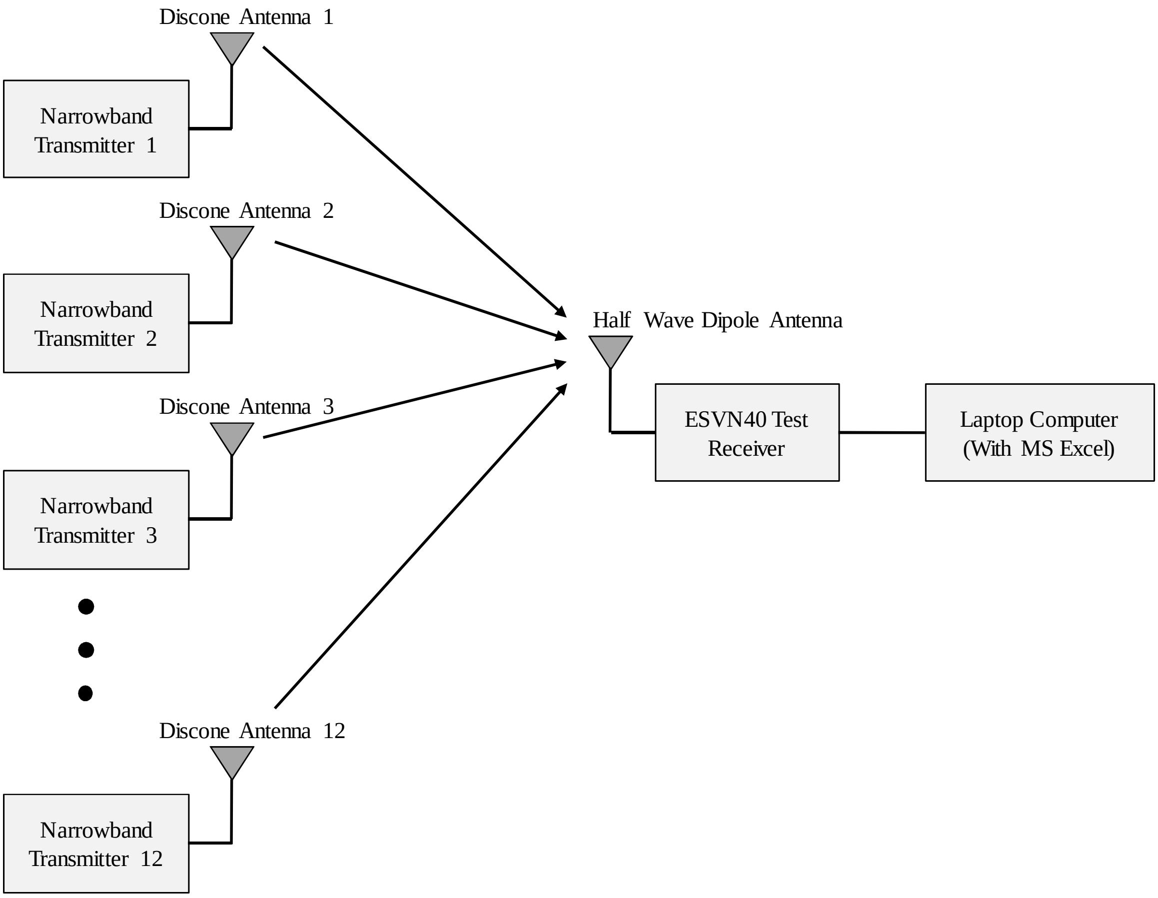


Figure A.1: Narrowband measurement system setup.

Appendix B

Additional Results for Chapters 8-10

This appendix presents additional results for the investigations performed in Chapters 8-10 of this thesis. In the chapters, the optimisation results of System Models A-D for Case Study 2 were presented for five discrete scenarios corresponding to 5, 10, 15, 20 and 25 active users or Erlangs of traffic. The purpose of this appendix is to present the optimisation results for all the scenarios from 5 to 25 active users or Erlangs of traffic. The additional results for Chapters 8, 9 and 10 are shown in Figs. B.1, B.2 and B.3, respectively.

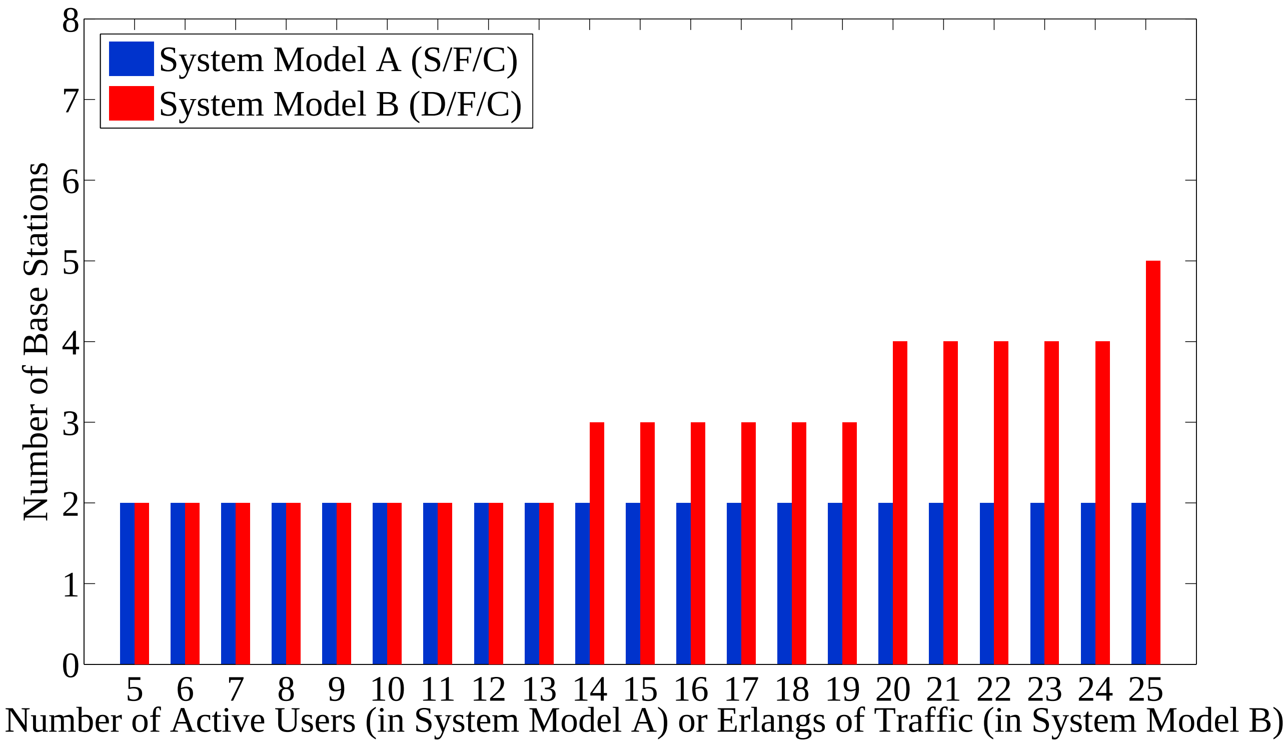


Figure B.1: Additional optimisation results of System Models A (S/F/C) and B (D/F/C) for Case Study 2.

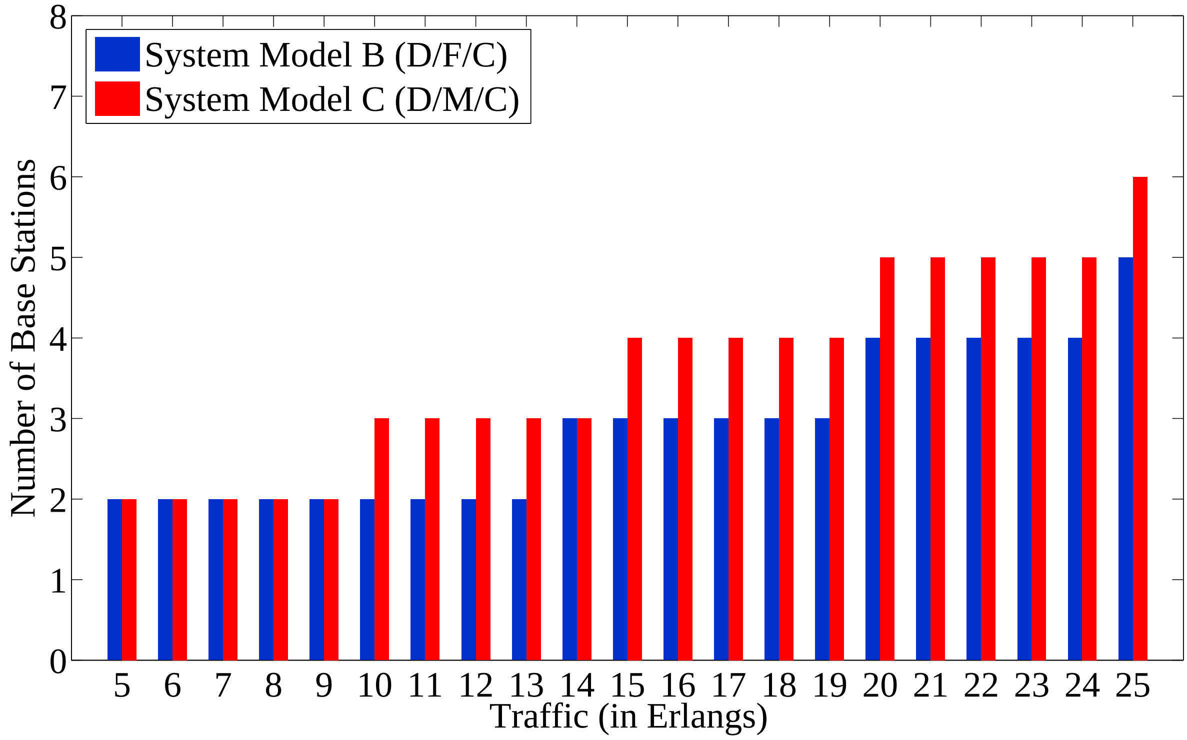


Figure B.2: Additional optimisation results of System Models B (D/F/C) and C (D/M/C) for Case Study 2.

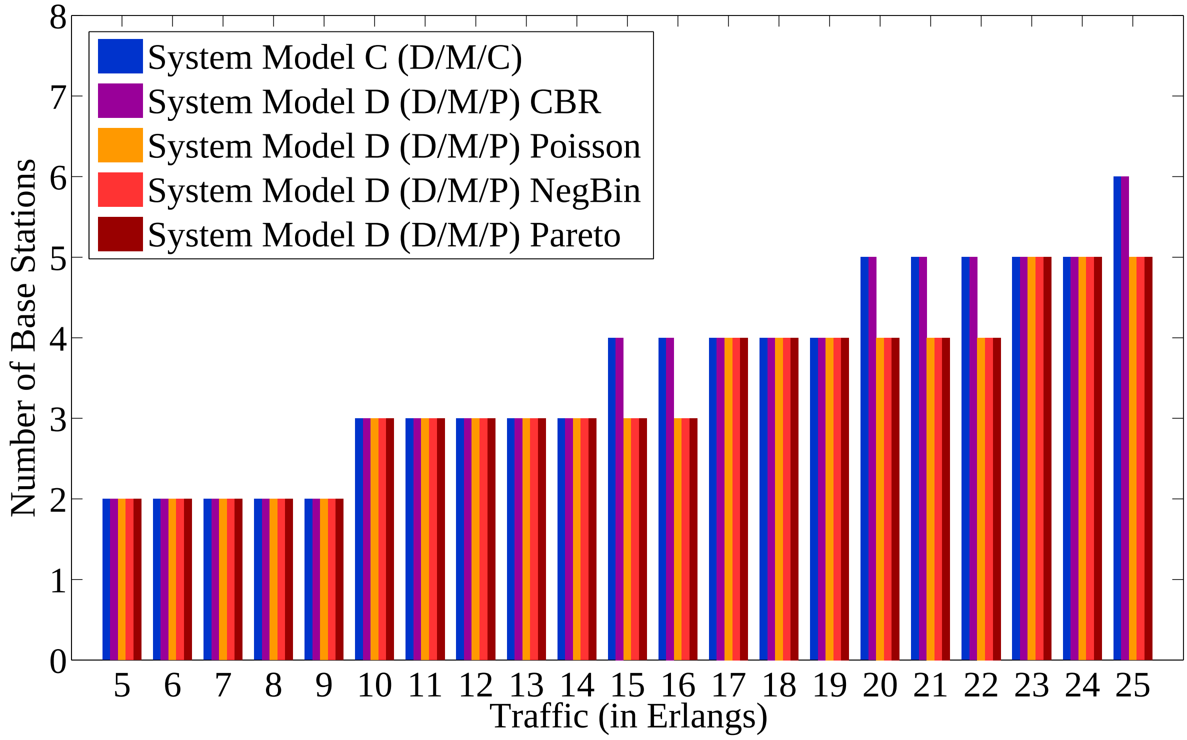


Figure B.3: Additional optimisation results of System Models C (D/M/C) and D (D/M/P) for Case Study 2.

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