Summary

Network operators desire effective, pragmatic solutions to instances of the cell planning problem in order to improve their quality of service, enhance network coverage and capacity capability, and ultimately increase company profits. Previous cell plans have been constructed manually but these methods do not produce the best network configuration. More reliance has since been placed on automated cell planning to produce effective solutions. The introduction of the Universal Mobile Telecommunication System (UMTS) emphasizes the need for high performance planning tools.

Motivated by a discussion of the literature concerning cell planning, an existing model for Global System for Mobile Communication (GSM) is modified to take account of the requirements of UMTS networks. A suite of test cases is created using a purpose-built problem generator, including problems with a range of site and traffic distributions for rural, suburban and urban markets.

Traditionally, cell planning has been seen purely as an optimisation problem, neglecting the pre-optimisation stage of network dimensioning. This thesis investigates the effect of network dimensioning as a precursor to optimisation demonstrating the benefits of cell planning in three stages consisting of site estimation, site selection and optimisation. The first stage, site estimation, utilises previously published lower bounding techniques to provide a means of approximating the number of sites required to meet capacity targets in the uplink and downlink. Site selection compares random selection to three newly developed algorithms to make effective automatic selections of sites from a candidate set. The final optimization phase presents a framework based on the tabu search meta-heuristic capable of optimising the dimensioned network designs with respect to the representative operational scenarios. Multiple traffic snapshot evaluations are considered in the optimisation objective function.

Declaration

This work has not previously been accepted in substance for any degree and is not being concurrently submitted in candidature for any degree.

Signed ..K. E. Oliver............ (candidate)

Date 14-03-06

Statement 1

This thesis is the result of my own investigations, except where otherwise stated. Other sources are acknowledged by explicit references.

Signed ..K. E. Oliver............. (candidate)

Date 14-03-06

Statement 2

I hereby give consent for my thesis, if accepted, to be available for photocopying and for inter-library loan, and for the title and summary to be made available to outside organisations.

Signed .K. E. Oliver.......... (candidate)

Date 14-03-06

UMTS Network Optimisation

Kathryn E. Oliver

A thesis supervised by Dr S. M. Allen and Prof. S. Hurley and submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy in the University of Wales.

Centre for Intelligent Network Design
Cardiff University School of Computer Science*

September 2005

*Queen's Buildings, 5 The Parade, Roath, Cardiff CF24 3AA, U.K.
Tel: +44 (0)29 2087 4812 Fax: +44 (0)29 2087 4598 Email: office@cs.cardiff.ac.uk

Acknowledgements

I would like to express my gratitude to Prof. Steve Hurley and Dr Stuart Allen for their help and support. I would also like to thank the following people for their support and friendship: Prof. N. Fiddian; Claire and Richard; colleagues at Cardiff University School of Computer Science especially in the Centre for Intelligent Network Design; Simon, Rupert and Steve; Jess; Keith and Eileen; and a special thank you to Mam, Dad, Sarah and Ian for their unwavering love and encouragement.

I would like to dedicate this thesis to my parents with all my love.

Contents

List of Figures

List of Tables

LIST OF ALGORITHMS

Notation

The notation listed is introduced and used between chapter 3 and chapter 6.

A_k	Antenna at s_i
A_k^β	Angle of tilt of antenna A_k
$a(c_k)$	Area of a cell c_k
A_k^δ	Azimuth of antenna A_k
α_j	Orthogonality of channel between mobile station user u_j and serving antenna A_k
β	Tilt of an antenna
C	Set of cells
c_k	Cell belonging to A_k
δ	Antenna azimuth
D	Set of desired points
d	Desired/target cell load
E	Estimated number of sites from site estimation process
e	Cost function
E_b/N_o	Signal energy per bit by noise spectral density
E_c/I_o	Pilot signal to noise ratio
e_n	Component n of cost function
e_{new}	Cost of current network design
e_{old}	Cost of previous network design
ϵ	Angle from the horizontal to a service test point
ϵ'	Horizontal angle between a service test point and the antenna azimuth
η_{DL}	Downlink load

$\eta_{DL}(c_k)$	Downlink load of c_k
η_{UL}	Uplink load
$\eta_{UL}(c_k)$	Uplink load of c_k
f	A service
γ	Vertical angle of incidence
G^{A_k}	Transmission gain of the antenna A_k
g_j	Gain experienced at u_j
H	Signal range in kilometres
I_j^{DL}	Interference ratio experienced at u_j
$I^{UL}(c_k)$	Interference ratio of c_k
κ	Proportion of simultaneously active users per square kilometre
$\kappa(f)$	Proportion of simultaneously active users utilising service f
$\kappa(M)$	Proportion of simultaneously active users in the service area
λ_f	Proportion of users utilising service f
$L_h^{A_k}$	Horizontal loss value of antenna A_k
$L_v^{A_k}$	Vertical loss value of antenna A_k
L^{A_k}	Transmission loss of the antenna A_k
l_j	Loss experienced at u_j
M	Service area
m	Allowed margin above desired/target cell load
μ	Percentage of power allocated to the pilot channel
N	A network
$n_A(s_i)$	Number of antennae located at s_i
$n_A(S)$	Number of antennae located at a general site s
n_D	Number of desired points
n_f	Number of services
n_{op}	Number of operational antennae
n_S^{op}	Number of deployed sites
n_S	Number of candidate site locations
n_T	Number of service test points
$n_u(c_k)$	Number of mobile station users in c_k
$n_u(f)$	Number of users with service

$n_u(M)$	Number of users in M
$n_u(\text{template})$	Number of users covered by the template
P^{A_k}	Power setting of A_k
$P_k^r(i)$	Downlink received power
Q	Propagation loss
$Q_{(i,k)}$	Propagation loss between t_i and A_k
$Q_{(k,i)}$	Propagation loss between A_k and t_i
$R(N)$	Total downlink bit-rate in network
$r(N)$	Total uplink bit-rate in network
R_j	Downlink bit-rate of the service used by mobile station user u_j
r_j	Uplink bit-rate of the service used by mobile station user u_j
$R(f)$	Downlink bit-rate of the service f
$r(f)$	Uplink bit-rate of the service f
S	Set of all candidate sites
s_i	an operational site
σ_f^{DL}	Downlink load calculation for a service f
σ_f^{UL}	Uplink load calculation for a service f
T	Set of service test points
t_i	A service test point
u_d	User density
u_j	Mobile station user
v_j	Activity factor of u_j
χ	Half the base of a hexagon
W	WCDMA chip rate
w_n	Weight of component E_n
(X,Y)	Cartesian coordinates of a site
(x,y)	Cartesian coordinates of a service test point
Z	Network design or configuration
Z_{init}	Initial network design
Z_{new}	Current network design
Z_{old}	Previous network design
$\zeta(Z_{old})$	Neighbourhood of Z_{old}
$Z_{init}(Z_{old})$	Benchmark neighbourhood of Z_{old}

Chapter 1

Introduction

With the proliferation and development of cellular radio networks effective and pragmatic solutions to instances of the cell planning problem are desired by network operators who aim to improve quality of service, enhance the network's coverage and capacity capabilities, and ultimately increase company profits. To improve their chances of commercial success, they need to place more emphasis on ensuring that informed decisions are made with respect to the design of cellular networks.

The engineering of a cellular network is comprised of several related tasks including the selection and configuration of a set of sites from a candidate list of locations that have been identified by the network operator as potential sites for deployment. Site locations have associated costs resulting from restrictions in acquiring property at key locations that are normally affected by high prices and local demand. The selected sites form the basis of a cellular network that will need to satisfy certain performance and quality requirements at roll-out and for the duration of the network's deployment.

Network designs are often developed manually by network planners aided by network planning tools, but these methods rarely produce the best network configuration. More reliance has since been placed on automated cell planning solutions in order to produce more effective solutions to this computationally hard problem and the introduction of *Universal Mobile Telecommunications System (UMTS)* networks emphasizes the need for high performance planning tools.

Traditionally the cell planning problem has been seen purely as a single stage optimisation problem, however the pre-operational stage of cell planning also includes network dimensioning which involves deciding how many sites are required to meet subscriber service demands. The network dimensioning stage precedes the next two stages of site selection optimisation and network configuration optimisation. This thesis takes an alternative approach to the existing literature by investigating for the first time the cell planning problem in three distinct stages consisting of network dimensioning, site selection optimisation and network configuration optimisation. In general the approach involves analytically assessing the cell planning problem to determine the required number of sites this reduces the number of network design solutions considered thereby increasing prospects for tractability.

The main contribution of the thesis is to determine if network dimensioning techniques can be effectively applied as a precursor to optimistation, specifically addressing the application of lower bounding techniques to provide an estimate of the number of sites for selection. Recommendations are made with regards to using the first stage independently (as part of a stand-alone analytical dimensioning tool) or as the first stage of a complete cell planning process (as illustrated in Figure 1.1). The research continues by applying a number of methods to make effective site selections, using the estimate, from the available candidate sites. The third stage involves the development of an optimisation framework capable of optimising the dimensioned networks produced from the preceding stages. Finally, after a specified time optimising the network's configuration it is possible to determine if networks formed from less effective site selections can be significantly improved during optimisation and possibly surpass any initial advantage in making more sophisticated site selections.

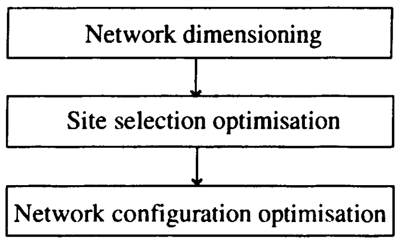


Figure 1.1: Cell planning in three stages.

The remainder of the chapter defines the cell planning problem along with its objectives and discusses the differences between manual and automated network design. The planning process for cellular networks is discussed specifically for *Global System for Mobile Communication* (GSM) and UMTS networks highlighting the added challenges of third generation cellular network planning required for UMTS. The chapter concludes by explaining the structure of the remaining chapters.

1.1 The cell planning problem

The cell planning problem is also known as the network design problem, the network planning problem, the antenna positioning problem and the radio coverage problem. Formally, solutions to the cell planning problem attempt to design a network, composed of sites selected from the set of all candidate sites such that certain objectives such as coverage, capacity and quality of service, can be met with respect to a given subscriber traffic demand.

Fundamentally, the aim of the cell planning is to select a subset of sites from a specified candidate set and for each selected site determine a suitable number and configuration of antennae. The signal transmitted by each antenna is received by a number of mobile station users located within the antenna's coverage area. Normally, a mobile station will select the site at which an antenna is located that transmits the strongest signal. The region of the service area for which an antenna provides the strongest signal is called a *cell.* The cell area of each antenna in the network is calculated and the set of regions produced is called the *cell plan* and thus the process of planning cellular networks is called *cell planning.*

As previously stated the selection and configuration of sites form the basis of a cellular network that must satisfy certain network design objectives. To design a good network a number of competing objectives could be considered include:

- maximising quality of service provided to subscribers;
- maximising coverage;
- maximising capacity;
- minimising infrastructure outlay;
- maxmising revenue;

◦ minimising expenses.

Network *coverage* is determined by the proportion of area that receives signal above the operator's specified threshold. This can be determined, for example, by operator drive tests that record the penetration level of signals in different regions of the network, however some regions will be too difficult to reach preventing signal measurement. Propagation conditions affect coverage, especially in urban areas where there may be many high rise buildings that can significantly attenuate the signal. It is important that network planning is undertaken to ensure that high coverage networks are produced.

Network *capacity* is determined by the number of subscribers that can receive and make a call when required for both voice and data services. Methods to improve network capacity can involve introducing new sites to the network or altering the infrastructure configuration at existing sites. If the signals received from simultaneous calls are too strong, then there is the potential for *interference*. This corresponds to multi-coverage of regions of the service area and will affect the potential quality of reception in addition to increasing the number of configured sites that are deployed in the network.

The primary outlay for an operator is acquiring, deploying and maintaining sites. Along with these financial constraints, increased public health fears provide network operators with increased motivation to reduce the number of sites deployed. Selecting good locations for sites is a key factor in the design of cellular networks. This can be especially difficult in cities where buying or renting property is subject to high prices and competition from other prospective buyers. Sometimes operators specify the reuse of existing site locations when rolling out a new network and this provides an added planning constraint. Solving the problem and meeting each of the objectives is difficult and it is left to the network operator to define each of the objectives and their relative importance.

1.2 MANUAL CELL PLANNING

Traditionally networks have been designed manually by a network planner. Usually the network planner is assisted by a planning tool that contains a computerised model of the network and allows the planner to determine the affect of adjusting the configuration of a number of the network's antennae. As there are so many different parameters that could be adjusted the number of network design possibilities that can be considered by the planner, in a reasonable time, is very small.

A network design can be altered in a number of different ways, some of which include:

- antenna power settings can be increased or decreased within a predefined range;
- antenna tilt settings can be increased or decreased within a predefined range;
- antenna azimuths can be rotated;
- antennae can be activated and deactivated;
- antenna models can be changed.

To illustrate the complexity involved there are typically 10,800 possible settings available to a network designer when configuring a single antenna with 10 possible power settings, 15 tilt settings and 72 possible azimuth settings. Consider a network that required 20 antenna, the number of possible network designs available is approximately 10^{80}. Network planners need to consider networks with many more sites, in order to model the network in detail and meet the planning objectives. Solving the cell planning problem via exhaustive search is clearly intractable and this emphasizes the need for high performance automated cell planning tools based on heuristic methods.

1.3 AUTOMATIC CELL PLANNING

As previously stated manual planning already involves the use of computerised planning tools thus automatic cell planning does not simply constitute using a computer to help plan a network. Instead automatic cell planning goes a stage further using a computer system, which contains a model of the network, to automatically evaluate many possible network configurations with respect to a certain traffic scenario. The user is then presented with the best of all the network designs considered by the automated cell planning tool. Therefore the use of computers to help provide automated solutions is conducive to cell planning.

Modelling cell planning often presents a trade off between abstraction and detail. Abstract models have previously been used to model cell planning mathematically using techniques from graph theory, set theory and integer linear programming. A network planner working for an operator may take a detailed approach to modelling the network as the results have to be accurate, but a more abstracted approach could be useful for estimating the number of sites required or the process of evaluating a network. Either way, a planning tool must be capable of accurately modelling the cellular network when provided with network design parameters and traffic demand scenarios.

Many approaches to automated cell planning have been addressed in the literature [10, 11, 22, 42, 56, 59, 65] and these along with others are reviewed in Chapter 2. Typically, cell planning solutions incorporate only an optimisation stage. Network optimisation in automated cell planning is concerned with providing a process to improve the performance of a network, using desired quality of service targets to measure the network's performance and assist in finding the best possible network design. Sophisticated techniques can be applied to network optimisation through the use of heuristic and meta-heuristic solution techniques such as genetic algorithms, hill climbing algorithms, simulated annealing and tabu search. However, approaches to automated cell planning should not only consider an optimisation stage, but also consider developing useful techniques for determining the infrastructure requirements when establishing new and developing existing networks. This preceding stage is often referred to as *network dimensioning.* The main objective of dimensioning is to simplify the complex task of network planning by making the necessary estimations and assumptions concerning the hardware or resources required to provide a satisfactory service. In this work network dimensioning is defined as the process of determining an initial estimate of the number of sites required for site selection optimisation.

1.4 CELL PLANNING FROM GSM TO UMTS

To date, three generations of mobile phone networks have been introduced [88]. First generation systems (1G) started in the 1980s and were based on analogue transmission techniques. In the early 1990s second generation networks were deployed, with Europe introducing GSM with the aim of providing a unified standard.

Initially, GSM provided a voice only service and later evolved to meet the requirements of data traffic and other services by producing the following enhancements: GSM and Value Added Services (VAS); GSM and General Packet Radio Services (GPRS); and GSM and Enhanced Data rates in GSM Environment (EDGE).

As a result of not being designed for multimedia communication, GSM is limited in its ability to efficiently accommodate the increased demand for data services such as web browsing, picture messaging and video conferencing. Fortunately, in the early 1990s, the International Telecommunications Union (ITU) had the foresight to define a new standard for third generation (3G) mobile networks. The resulting *wide-band code division multiple access* (WCDMA) standard was designed from the outset to accommodate a wide range of services. This together with the continuing evolution of GSM networks will create new business opportunities for operators.

Since the introduction of second generation cellular systems significant expertise has accrued in network planning. The complexity of the network planning problem is increased when third generation networks are considered. Currently, operators are coming to terms with the new challenges involved in deploying UMTS networks in a cost effective manner. The downturn in the global economy, the large licence fees paid for spectrum and increased competition means that balancing financial constraints and quality of service is more important than ever. Radio network planners face a number of new challenges in the move from second generation networks to third generation networks. The differences between GSM and UMTS cell planning are discussed in detail by Berruto, Gudmundson, Menolascino, Mohr, and Pizarroso [12], Oliver, Hurley, and Allen [67], Santos Pinto [75], and Spilling and Nix [81].

To provide capacity by enabling sharing of the medium by multiple communications occurring in a network, and to do this without creating too many problems such as interference or call-blocking a *multiplexing scheme* is employed. GSM networks employ *frequency time division multiple access* (FTDMA) as the multiplexing scheme, which involves the discretization of the frequency spectrum and time. The use of FTDMA requires channel assignment [43] where frequencies are used to distinguish between the communications of different users. Network planning in GSM is therefore normally a two stage process with one stage involving coverage planning and the other involving capacity planning. In coverage planning, a frequency plan is subsequently generated to mitigate interference and hence reduce call blocking/dropping. That is, the frequency plan can improve the operational performance in light of interference that has not been accurately predicted during the initial design. The capacity of the network can also be increased via *cell splitting*, which involves reducing the cell sizes by adding extra transmitters to the service area.

UMTS networks employ WCDMA, the newest and most complicated of the multiplexing schemes. In WCDMA each user is assigned a unique code and these codes can be transmitted on the same channel. As such, WCDMA uses one frequency, whilst FTDMA uses many. The codes are transmitted simultaneously, and each recipient can decode only the signal they require by using the mathematical properties of the code. Other recipients' signals appear only as background noise. The large number of possible codes available means that this method has high security, with many communications occurring simultaneously.

As a frequency plan to reduce the interference does not exist in WCDMA networks, capacity and coverage objectives have to be considered simultaneously during network planning and optimisation. In GSM networks a cell has a fixed size, however with the use of WCDMA technology in UMTS the size of a cell is dependent on the traffic load at any moment in time; for example when a cell is highly loaded the coverage area of the cell will be much smaller than times when the cell is lightly loaded. This dynamic process is referred to as *cell breathing* and is the reason coverage and capacity have to be considered simultaneously when planning UMTS networks. Therefore balancing the traffic load amongst each cell and ensuring sufficient area coverage relies heavily on the adjustment of site positions, antenna configurations, power levels, radio resource management (RRM) algorithms and *handover.*

Handover occurs when a call has to be passed from one cell to another as the user moves between cells. In a traditional *hard* handover (use in GSM networks), the connection to the current cell is broken, and then the connection to the new cell is made. However, as a result of dynamically changing cells in WCDMA based systems it is important (for example if a cell suddenly becomes to heavily loaded) that there is an option to handover a number of calls to neighbouring cells. Since all cells in WCDMA use the same frequency, it is possible to make the connection to the new cell before leaving the current cell this is known as *soft* handover. Soft handovers require less power, which reduces interference and increases capacity.

Handover is therefore an important planning objective in WCDMA based systems.

UMTS networks were developed for the high data-rate services they could offer over GSM, GPRS and EDGE networks. When designing a network the planner has to consider the different service types available as the type of traffic will not be homogeneous in UMTS. GSM has voice dominated traffic with a small proportion of data services. However in GSM networks, a data channel consumes the same capacity as voice and the network planning does not change subject to the type of traffic. The main feature of UMTS networks involves how new data rate service areas are introduced. The interference caused by data-rate users is dependent on where the user is located in the cell, for example a mobile station user on the edge of the cell could cause increased interference for other mobile stations. Therefore research into cell planning for UMTS must consider mixed service scenarios and design networks that can handle increased traffic loads.

1.5 THESIS OBJECTIVES AND STRUCTURE

Manually developed network design solutions rarely produce the best network configuration. The aforementioned need to produce effective solutions for cell planning has led to a greater reliance on automated solutions. The introduction of UMTS networks further emphasizes the need for high performance planning tools. The added planning constraints mean that cell planning for UMTS is more complicated and as such network operators should place more emphasis on the benefits of developing automated cell planning tools. Traditionally cell planning has been seen purely as an optimisation problem and little attention has been paid to network dimensioning as a separate planning stage. This thesis aims to incorporate network dimensioning into a solution framework that can be used to solve instances of the cell planning problem for UMTS networks. The remainder of the thesis is structured as follows

Chapter 2 looks at approaches to solving the cell planning problem specifically for UMTS networks. Discussion focuses on network modelling, network evaluation, availability of representative network and traffic data sets, network dimensioning and an overview of optimisation techniques which have previously been applied to cell planning.

Chapter 3 introduces the network model and assumptions used and applied throughout the thesis. Representative network and traffic scenarios that are used in the remainder of the thesis are presented. A formal statement of the network evaluation process and network design objectives is also given.

Chapter 4 defines network dimensioning process, which involves a method for estimating the number of sites required. The application of a previously developed lower bounds tool is suggested and analysed.

Chapter 5 presents three techniques for initial site selection and provides an analysis of the effect of site selection optimisation on the model.

Chapter 6 presents a customised optimisation framework formed from techniques such as local search and tabu search.

Chapter 7 investigates the use of network dimensioning and site selection as a precursor to network configuration optimisation.

Chapter 8 consolidates the findings from the preceding chapters and provides suggestions for future development of the presented methods and techniques.

Chapter 2

Literature Review

In 1986 Whitehead [91] authored an article in the IEEE Communications Magazine that highlighted cellular system design as an emerging engineering discipline stating:

> "These methods are coming to form a distinct cellular engineering discipline that includes the theory and practice of frequency assignment, antenna sectors, power levels, traffic engineering, and so on."

Amongst other observations Whitehead presented a number of fundamental cell planning objectives, defined the cell planning problem as an optimisation problem and commented on the need for practical computer aids and analytical techniques to improve the planning process.

In the 1990s a number of companies started to produce software for network design and optimisation for GSM networks. This software is still being developed for GSM networks with the recent addition of software solutions for planning UMTS networks. Examples of such software solutions for network planning include Marconi Planet DMS, Optimi Wizard, Aircom Asset and Forsk Atoll. Insight to the techniques, methods and solutions incorporated in commercial cell planning software is normally limited to white papers and a small number of conference papers.

One of the first published academic research papers containing techniques and results for cell planning dates back to 1994 and was authored by Anderson and McGeehan [11]. Since then the literature has developed with many authors presenting a number of approaches for different planning scenarios, with particular focus on solutions for GSM networks [42, 44]. In 2001 Amaldi, Capone, and Malucelli [9] found that little research had been carried out for UMTS networks, with many of the early papers presenting simple models usually accompanied by a more detailed optimisation framework. The volume of research into UMTS network planning has since increased and a variety of modelling and optimisation techniques have been developed and applied.

This thesis addresses UMTS network modelling, static network evaluation, network dimensioning and network optimisation. The following sections discuss literature concerning:

- network modelling for UMTS;
- availability of network and traffic data sets;
- network dimensioning;
- optimisation techniques and applications;
- network evaluation.

2.1 APPROACHES TO NETWORK MODELLING

It is common practice to formulate mathematical models of real world problems to facilitate the implementation of automated solution techniques. Modelling techniques aim to encapsulate the operation of a cellular network into computable methods and objectives. The translation from the real world to a mathematical representation can often result in the loss of elements present in the original problem, meaning that choices pertaining to this abstraction must be carefully made so that solutions remain valuable for application in the operational situation. Techniques used to model and optimise a cellular network must be chosen in such a way that network infrastructure adjustments, suggested to solve the modelled situation and objectives, can be related back to the operational situation with reasonable accuracy and success.

The modelling of the cell planning problem has previously been split into two general approaches: abstract and direct. Abstract models tend to involve a mathematical approach, often relating the cell planning problem to set theory, graph theory or geometry, whilst direct modelling involves the representation of the cellular network upon which dimensioning, simulation and optimisation techniques can be applied. Both approaches, if modelled to a high granularity, can present solutions that very closely approximate the real world, but this is often detrimental to the computational complexity and time involved in finding a suitable solution.

A mathematical model is likely to produce a solution that is more elegantly defined than a direct model and tends to promote application independent solutions. However, this achievement can be limited due to the pre-processing required to identify the constraints involved in reaching a solution. Furthermore, the approach considers a subset of possible network design configurations reducing the solution space and thus eliminating a vast number of potential network designs.

2.1.1 DOMINATING SET PROBLEM

One abstract modelling approach involves the application of the *dominating set problem*, which has been used to relate test point coverage to a set of candidate sites with pre-selected configurations. This problem has been well studied independently of its application in cell planning and has been used to categorize the cell planning problem as NP-hard [17, 55]. Whitaker and Hurley [90] provide an overview of the dominating set problem along with other abstract and direct models for cell planning. One limitation of the dominating set approach which is inherent in abstract modelling, is that the solution found is only as good as the transmitter configuration set provided. Mathar and Niessen [55] and Reininger and Caminada [72] successfully apply the minimum dominating set problem to cell planning.

2.1.2 GRAPH THEORY

An alternative approach to the dominating set problem involves the use of *graph theory* [32]. This allows a graph to be built where an interdiction rule is specified. For example, sites are represented by vertices on a graph and if there exists an edge between two sites, a constraint is formed that prevents the two sites from being simultaneously included in the final solution. A solution corresponds to a set of sites where each pair of sites does not violate the interdiction rule; translated in terms of graph theory this means finding an *independent set.* This representation can be used to control interference and handover in a cellular network model. An example of this approach is provided by Chamaret, Josselin, Kuonen, Pizarroso, Salas-Manzanedo, Ubeda, and Wagner [20] whose planning objective is to provide adequate coverage. The difficulty with this approach is determining which sites can be found together when forming an independent set.

2.1.3 Mathematical programming

Discrete mathematical programming approaches have been used as a direct modelling approach to solving the cell planning problem and are often adopted by researchers with an interest in operational research and stochastic methods. Mathematical programming involves the use of mathematical models, particularly optimisation models, that assist decision making. For cell planning using mathematical programming, discrete decision variables are used to represent components of the model and network. A branch of mathematical programming that is frequently used is linear programming, which involves linear relationships between decision variables.

A number of authors formalise the cell planning problem as integer programs [10, 52, 56, 92], considering it a mathematical optimisation problem. Direct models applying mathematical programming were developed for GSM by Mathar and Niessen [55] and were later adapted by Mathar and Schmeink [56] for application in a UMTS network (although the model was still fairly general). Mathar and Schmeink [56] assert that for large problems the integer linear programs are often too complicated to allow for a globally optimal solution to be found. To approach this problem they introduce a *branch-and-bound* algorithm [69] that calculates a feasible solution in acceptable running time.

2.1.4 Component based approach

An alternative direct modelling approach is normally adopted by computer scientists and electronic engineers. This type of direct modelling typically removes the need for pre-processing by involving the modelling of only the necessary components of a cellular network, and tends to require the careful management of large data sets and derived results for analysis. This type of model is normally incorporated into an optimisation framework that addresses multi-objective optimsation by generating a cost or objective function that acts as a indicator of the quality of each considered potential network configuration. Heuristic and meta-heuristic approaches can then be employed to achieve suitable solutions and can be defined as follows:

- a heuristic is a method that seeks a near optimal solution from a set of solutions or solution space, at a reasonable computational cost, without being able to guarantee optimality, closeness to optimality or the solution's feasibility in the real world.

- a meta-heuristic is a high-level algorithmic framework that can be customised to solve optimisation problems.

Meta-heuristic approaches can be applied to both abstract and direct models and are discussed along with exact and heuristic approaches in Section 2.4. Network models developed according to this approach are demonstrated by Reininger and Caminada [73], Rawnsley and Hurley [70], and Hurley [42].

The main distinction between these two direct approaches, mathematical programming and component based modelling, lies in the amount of effort involved to achieve a suitable solution. Mathematical programming can be problematic when trying to model the required dependencies between network and traffic components. Bearing this in mind a meta-heuristic approach is likely to require less effort in adapting it to suit the approach taken by Reininger and Caminada [73] and Hurley [42]. Although adapting the meta-heuristics to suit the model is crucial to the effectiveness of this technique.

Reininger and Caminada [72] and Reininger *et al.* [74] provided a cell planning model for a general scenario, which was adapted and applied to a GSM network by Hurley [42] but nobody has taken this modelling approach for UMTS networks. The modelling approach employed in Chapter 3 is classified as a direct component based approach. It involves the modelling of relevant physical components of a cellular network with the subsequent application of newly developed network dimensioning techniques allowing final incorporation into an optimisation framework, as presented in Chapter 6.

2.2 DATA SETS

Network and traffic data sets are in short supply within the public domain, as operators tend to keep confidential their configuration data and measured or predicted traffic scenarios. This makes research into automated cell planning more difficult, resulting in researchers having to develop their own data sets or modify available legacy data sets from GSM networks for UMTS network planning. As a result, many of the assumptions made in generating the data sets are not detailed in the literature making it difficult to identify the author's assumptions.

Recently the issue of network data set availability was addressed by the EU-project Momentum [54], in which a collection of data concerning UMTS network design, covering environment, services and traffic, was developed and published by Eisenblätter, Geerdes, Koch, and Türke [25]. They published a number of traffic and network data* sets specific to UMTS networks and services. The data sets were subsequently used by Eisenblätter *et al.* for testing purposes with their UMTS cell planning tool. The data sets are comprehensive but although they are published in XML they are not easily adapted to existing model implementations. Evidence of the data sets being tried and tested by other authors is not yet available.

Many authors fail to state the origin of their network data sets or describe them incompletely [17, 58, 46]. The list below demonstrates the differences in information provided by various authors:

- Calegari, Guidec, Kuoen, and Wagner [17] consider a 70 by 70 kilometre square service area for a scenario consisting of 150 candidate base stations each configured with an omnidirectional antenna;

- Molina, Athanasiadou, and Nix [58] consider a 500 by 700 metre square service area containing 70 control nodes for 7 candidate base station locations;

- Amaldi, Capone, and Malucelli [9] consider three differently sized service areas: 400 by 400 metre square, 1 by 1 kilometre square and 1.5 by 1.5 kilometre square, each for 22 candidate sites with 95 test points.

*These data sets were released after model implementation and experimentation had commenced, which prevented them being utilised in this work.

- Jamaa, Altman, Picard, Fourestie, and Mourlon [46] consider 45 and 115 sectored sites in a dense urban environment.

As authors provide different scenario information and vary in their definitions and understanding of terminology it makes comparison of results very difficult and reproduction of exact scenarios impossible.

2.3 TRAFFIC MODELLING

Traffic scenario data are as difficult to obtain as network data and collectively this is a serious impediment to research. As a direct result it is very difficult for other researchers to challenge proposed solutions and concepts, and form benchmark data sets and solutions. However, there are a number of publicly available traffic data sets for UMTS networks and these are discussed in the following sections.

In 2000, Butt and Woodfield [16] presented the Guildford test network that was established by Ericsson Telecommunication Limited. The test network consists of three sites, each configured with three directional antennas that are required to serve a small number of mobile stations. The mobile station traffic data was real measured data gathered and collated by Ericsson. The size of the data set is a limitation and is considered to be too small for testing algorithms. Since then the Momentum project has published traffic data that includes three publicly available traffic scenarios recorded for Berlin, Lisbon and The Hague. This data set provides service and traffic data which is characterised by uplink and downlink data rates, link quality and a stochastic data source model. Even though this network is available there is a need for more publicly available measured or predicted data sets.

When access to data sets or real-life test networks is limited, most authors turn to generating traffic data by making sensible decisions on the traffic distribution within the service area. A number of authors distribute their mobile stations across the service area uniformly, randomly or linearly [18, 35, 36, 48, 53, 56]. Tutschuka, Leibnitz, and Tran-Gia [85] claim that most network planning tools neglect design issues such as user behavior, demand distribution or core network design, and do not address the strong interaction between all the design factors. Indeed, many authors neglect to specify important information about the distribution in use, such as the user density or service demand. This information is likely to be available in an implicit sense but is rarely explicitly documented [5, 87, 94, 95].

Tutschuka *et al.* consider traffic modelling to be of equal importance to network modelling in the cell planning process. Motivated by the lack of traffic modelling, they introduce the idea of demand nodes for quantitatively describing traffic [84, 85]. This concept involves traffic being represented by a finite number of demand nodes, each of which have the same traffic demand. This allows densely populated areas to be represented by clusters and less populated areas, such as rural areas, by sparsely positioned demand nodes. Tutschuka *et al.* present a pictorial example of the distribution and discuss the process for constructing the distribution pattern. A number of authors have adopted this notion of demand nodes for traffic representation [55, 58].

The availability of easily accessible data sets is limited and careful consideration needs to be applied to modelling and generating data sets based on informed assumptions. This motivates the generation of network and traffic data sets presented in Chapter 3.

2.3.1 SITE ESTIMATION

In 1998 Reininger and Caminada [72] discussed the need for a network dimensioning stage in cell planning pointing out that the dimensioning step supplies the amount of resources required for the design when taking a component based approach to network modelling. In 2002 Laiho, Wacker, and Novosad [50], who promote a practical approach to network design, stated that the target of network dimensioning should be to provide a rough estimate of the number of sites required for selection. Although this viewpoint is often acknowledged in the literature, Laiho, Wacker, and Novosad's recommended target is rarely achieved [3, 14, 15, 29, 79]. This provides the initial motivation to pursue more practical approaches to network dimensioning that are of immediate use to a network designer.

Traditionally, analytical techniques for estimating the number of sites have focused on coverage predictions involving link budget analysis [3, 41, 50, 82]. As this area has been reasonably well-studied, it is not considered further in this work, which instead turns its focus to capacity dimensioning. Capacity analysis has become a more popular often being performed for the uplink [14, 38, 68]. In 2001, having previously concentrated on characterisation of uplink capacity in a WCDMA network, Burley [15] emphasized that downlink capacity estimation had largely been neglected (exceptions include [39, 51]) and that dimensioning of the downlink was more challenging compared to uplink. This observation was soon confirmed by both Kromer [48] and Molkdar, Burley, and Wallington [61], who suggested that capacity limitations within a UMTS network are often the result of the asymmetric nature of services, which are generally a higher rate in the downlink *e.g.* web browsing. Since then a number of authors have chosen to look at capacity analysis for the downlink too [7, 48, 61, 64, 66]. Networks can be limited by the uplink or the downlink and this is largely scenario specific, highlighting the need to be able to dimension a network based on the capacity constraints of both links. A complete process for dimensioning both the uplink and the downlink has not previously been presented in the literature and this omission motivates the development of the network dimensioning process presented in Chapter 4.

Capacity dimensioning normally involves formulating pole capacity* equations to obtain the maximum capacity of a cell [15, 14, 48, 64, 79]. Authors who adopt this approach obtain the maximum capacity of a cell, but fail to take the extra steps required to meet Laiho, Wacker, and Novosad's [50] dimensioning target by specifying an estimated number of sites for selection.

A good estimate of the number of sites required for deployment is likely to provide a useful starting point for further network planning and tuning. When this is one of the targets of network dimensioning it becomes homologous with techniques for determining lower bounds on the minimum number of sites required for use in an operational network. The only difference is that the result of determining lower bounds is to provide a minimum number of sites required to meet a desired network performance target, whereas site estimation for network dimensioning simply looks to determine a reasonable estimate of the number of required sites. In light of the similarity between lower bounding techniques and site estimation in network dimensioning, work in Chapter 4 considers the application of lower bounding techniques as a first stage in network dimensioning.

The only known published bounds for second generation systems, considering

*Pole capacity is the theoretical maximum capacity of an individual cell in the WCDMA network.

both coverage and capacity, were initially given by Allen *et al.* [8] and improved upon in Whitaker and Hurley [89]. Hurley [42] went on to use the second generation lower bounding techniques to determine the minimum number of sites required and used this as an estimate of the number of sites required to generate an initial network.

Producing a lower bound for UMTS networks is made more difficult as the distribution, density and traffic demand for each mobile station user has to be considered for both the uplink and the downlink transmission channels. However, in 2002 Allen, Hodge, Hurley, and Whitaker [7] published, in collaboration with the UK's Radiocommunications Agency* [4], lower bounding techniques for estimating the number of sites required to satisfy capacity and coverage targets in a UMTS cellular network. The capacity estimation process they developed uses uplink and downlink loading calculations to estimate the maximum cell size that can support the required traffic. Unlike other authors, Allen *et al.*, having calculated the maximum capacity of a cell, go on to compute the number of sites and antennae required to provide adequate service. Thus the application of this lower bounding technique is considered as the first stage in network dimensioning process presented in Chapter 4. Allen *et al.* presented the technique as a stand-alone estimation tool, which has not been compared to results obtained from a network simulation therefore the usefulness of the lower bounding technique is undetermined. This will be investigated using the network model for representative network and traffic scenarios in Chapter 3.

2.4 OPTIMISATION

This section provides an overview of solution techniques frequently applied to cell planning and highlights the optimisation methods used later in the thesis. It is not an exhaustive survey of optimisation techniques, but highlights the more successful techniques that are available and how they have been previously applied. Whitaker and Hurley [90] provide a more detailed survey of solution techniques available for cell planning in general.

*Duties of the RA were assumed by the Office of Communication (OfCom) in Dec. 2003 [62]

2.4.1 Exact approaches

A variety of algorithms exist that are capable of searching for an exact solution to a problem. Exact algorithms [71] (also called exhaustive or enumerative) are simple and generally the only requirement is to be able to generate all possible solutions to the problem systematically. In cell planning this involves being able to list all the feasible network design solutions, evaluate each, and select the best. In principle this is a good way to solve the problem, but not in practice due to the vast number of network design configurations available for any cell planning scenario that considers a realistic number of candidate sites.

Some popular optimisation algorithms like branch-and-bound are based on exact solutions and have been applied to GSM networks by Mathar and Schmeink [56]. For use in cell planning these solutions must eliminate all potential network designs that have undesirable modelling. Exact approaches have been applied to cell planning for UMTS by Molina, Athanasiadou, and Nix [58, 60] and by Anderson and McGeehan [11] for bench marking purposes. However, since the cell planning problem is NP-hard, such algorithms can only be run exhaustively for very small network test cases and are therefore rarely used in practice.

2.4.2 Heuristics

A large amount of work has been carried out on heuristic methods for solving combinatorial problems, with hundreds of papers written on the subject. *Sequential* methods use simple greedy heuristics to build a reasonable solution iteratively. Greedy heuristics approach solving a problem by constructing the complete solution in a series of steps. At each step the best decision available is made. These methods have the advantage of being easy to implement but must be designed for each specific problem and can often result in poor-quality solutions as exploration of the search space is inherently restricted; taking the best decision at each step does not necessarily lead to the global optimum. In UMTS cell planning, greedy heuristics are rarely used, but can provide a good comparison or benchmark technique for evaluating the performance of other heuristic algorithms [9, 10, 58].

The classification *deterministic heuristic* was used in [90] to group heuristics that obtain solutions by exploiting observations about the problem area and incorporate these to improve the performance of the network design found. Deterministic algorithms will produce the same result whenever the optimisation process is started from the same position, as there is no random decision process within the algorithm. Deterministic algorithms have also been frequently applied to UMTS cell planning [20, 27, 28, 44, 56, 58, 60] producing feasible solutions.

2.4.3 NEIGHBOURHOOD SEARCH AND META-HEURISTICS

Many heuristics are problem specific and as such attention has been given to the use of general neighbourhood methods for search purposes. A *neighbourhood search* or *local search* method starts from some initial solution and moves to better neighbouring solutions until it arrives at a solution which has no better neighbour, thus residing at a *local optimum*. Neighbourhood searches are easy to implement and usually reach a local optimum in relatively short computational time. However, the search is often of poor quality as it is unable to escape from local optima, preventing it from fully exploring the search space and finding a *global optimum*. *Hill climbing* is an example of a simple neighbourhood search algorithm that can be used to generate a sequence of network designs.

Implementation of hill climbing for cell planning requires a *neighbourhood* of *candidate* network designs to be defined that are a single *move* away from the current solution or network design. The type of move made is problem specific but generally involves changing one or more attributes of the current solution. In cell planning this alteration may consist of slightly changing the network design's parameters for example changing several antennas' parameters or activating/deactivating a an antenna. As a result the process for moving from one network design to another allows the local search space to be explored. A neighbourhood must be chosen such that it is capable of leading to good solutions without making the search too complex as a large neighbourhood is expensive to explore. A strategy for searching the neighbourhood is required, along with an evaluation function or *cost function* which determines the quality of a specific network design. At each iteration the best available network design in the neighbourhood is determined and selected by use of a cost function and then the process is repeated. The main disadvantage of this technique is that it is subject to becoming grounded in a local optimum. It has been recommended in the literature that this algorithm is run many times, each time starting at a different position in the search space.

Improvements to the basic hill climbing algorithm have resulted in *meta-heuristic* algorithms being developed [69, 71]. Meta-heuristic algorithms are a set of techniques that have been successfully applied to many diverse combinatorial optimisation problems, in each case achieving good solutions within large search spaces. They have been used to find acceptable approximations to the solution of many NP-complete problems. Meta-heuristic algorithms use problem specific criteria to guide the underlying heuristic towards a good solution, allowing it to escape local optima and search other areas of the search space to find global optima. When customising a meta-heuristic algorithm the choice of neighbourhood and the choice of cost function must be carefully made. Meta-heuristic methods such as simulated annealing and tabu search have received considerable attention and have been applied in many fields. In fact for cell planning the most frequently used meta-heuristics are tabu search [31], simulated annealing [2] and genetic algorithms [40].

Tabu search was developed by Glover in the 1970s and 1980s and is described by Glover, Taillard, and de Werra [31]. It differs from preceding methods by going beyond the criteria of terminating at a local optimum. The notion of exploiting certain forms of flexible memory to control the search process is the principle theme in tabu search. When looking to move from the current solution, the best solution is selected providing it is not *tabu* restricted. Tabu search maintains a history of the states encountered during the search and this helps to determine which solutions may be reached by a move from the current solution. A tabu move belongs to a history of tabu restricted moves and each move is forbidden for an individual tabu tenure (number of iterations). *Aspiration criteria* are also specified which allow a tabu restriction to be overridden if the solution under consideration is the best so far.

Tabu search algorithms perform well for many combinatorial problems and are suitable as an optimisation technique for the network planning problem [9, 52, 86]. Vasquez and Hao [86] use tabu search to optimise a GSM cell plan, whilst Lee and Kang [52] consider two different scenario environments, CDMA and AMPS. These authors take similar approaches when designing their move strategy, using moves that activate and deactivate antennae [9, 52]. Lee and Kang incorporate short term memory with two different tabu tenures and go on to show that the application of two diversification strategies is highly effective in attaining a 10% cost reduction. Lee and Kang claim that the choice of tabu tenure is crucial to the algorithm, whilst long term memory is helpful as it allows other areas in the search space to be considered. The general conclusion amongst these authors is that although tabu search needs to be tuned effectively and take into account short and long term memory, it remains a highly suitable and robust algorithm for cell planning.

Simulated annealing is used to find near-optimal solutions in large search spaces that are typically subject to many constraints. This technique is linked to thermodynamics concerning the process of annealing which involves the gradual cooling of metals to increase their strength. The slow reduction of temperature facilitates a stronger bonding of the metal. The analogy to optimisation is made by allowing most new candidate solutions or network designs to to be accepted at first but as the temperature cools the rate of acceptance declines.

Simulated annealing has been applied frequently for optimisation in cell planning. Anderson and McGeehan [11] first applied simulated annealing to cell planning considering a small test case consisting of four sites. In [11] comparison is made with an exhaustive algorithm to facilitate benchmarking and results highlight that starting the optimisation from different positions yields a number of different solutions, proving that near optimal solutions are not unique. Mathar and Niessen [55] applied simulated annealing when a suitable solution could not be found from an integer linear programming solution using CPLEX* [45]. Hurley [42] used simulated annealing to optimise a GSM network, indicating that the solution framework produced very high quality results. Akl, Hedge, Naraghi-Pour, and Min [6], after applying simulated annealing, claimed that the technique was computationally intensive and difficult to tune, but concluded that it is a feasible optimisation process for cell planning.

Genetic algorithms were initially developed thirty years ago and involve the use of algorithms based on natural selection. For cell planning a population of candidate network designs is produced, which are represented by a string of genes or chromosomes. As time passes the population of candidate solutions changes based on the use of biological evolution as a problem-solving strategy. When a candidate solution is selected it becomes a parent. Next, the application of genetic operators

*CPLEX is a mixed integer linear programming solver called mutation and crossover is used to evolve the solutions. *Crossover* involves combining aspects of parents' genes to produce off-spring; *mutation* involves randomly altering an off-spring's genes to introduce diversity.

Genetic algorithms perform well for most combinatorial problems and are suitable as an optimization technique for the cell planning problem. Genetic algorithms normally involve the optimisation of a single cost function that assists in creating a population of high performance solutions; the performance of a genetic algorithm relies on deciding on a suitable representation for the cell plan in a genetic form.

Genetic algorithms have been applied to cell planning in recent years [17, 33, 52, 58]. Reininger, Dony, and Caminada [74], who apply the dominating set problem as a modelling solution, continue to optimise with the use of a genetic algorithm. More recently Jamaa, Altman, Picard, Fourestie, and Mourlon [46] applied genetic algorithms for optimisation and, although they claimed the genetic algorithm had performed well, their published results indicated that their implementation did not consistently out-perform the manual planning approach they used as a benchmark.

In Chapter 6 an optimisation framework is presented that incorporates some of the aforementioned heuristics and meta-heuristics. Approaches to customizing the algorithms for use with the model presented in Chapter 3 are also outlined. The optimisation framework provides a basis for determining if methods for static network evaluation and network dimensioning are useful in automated cell planning.

2.4.4 SITE SELECTION

The process for identifying sites for deployment in a network is long and can result in a delay in network launch. Smith and Collins [80] discuss the site selection process, briefly listing the steps undertaken by a network operator including:

- ascertaining site locations;
- site qualification tests to ensure the sites are viable candidates;
- site acceptance and rejection;
- site deployment and configuration.

Candidate sites for automated cell planning can be obtained by generating site locations arbitrarily or by using a distribution or pattern. However, the process for estimating the number of sites required and selecting the most useful site locations is often not explicitly stated or explained by authors and the application of dimensioning techniques to help in making this decision is not evident.

Authors often state the number of sites they consider without providing details of the rationale for site numbers or locations. For example Hiltunen and de Bernardi [39] make use of 16 three-sector macro sites but fail to specify how the number of sites is decided or how the rationale for selecting the required sites is determined. Molkdar, Burley, and Wallington [61] make use of 37 three sector sites and, although it is stated that the sites are distributed randomly across the service area no explanation is provided of how the number of sites required for selection was decided.

A number of authors use more involved processes for site selection in order to determine a starting point for optimisation, for example:

- Amaldi *et al.* [9] who start their tabu search with an initial solution found either from using short runs of a greedy algorithm to find a network design or by randomly selecting an initial network design.
- Hurley [42] uses a number of different initial starting points including starting optimisation from a pre-existing legacy solution, by randomly selecting a pre-specified initial number of sites and from a solution that is known to satisfy coverage.
- Lee and Kang [52] start their tabu search optimisation from two different initial solutions, one with all sites active and the other with a selection of random feasible sites that collectively satisfy capacity and path-loss constraints.

These authors incorporate methods for evolving site selection into the optimisation stage with success and this approach has been well studied. As the sites selected change during the optimisation it is not easy to determine the effect of the initial site selections as the collection of sites deployed at the end of the optimistion period are rarely the originally selected sites. Furthermore, when time is spent during optimisation performing evolving site selection relatively less time is available to optimise the configuration of the existing sites.

Créput *et al.* [21] recently had success with site selection in a GSM network using a process of *adaptive meshing* which involves selecting sites based on a hexagonal pattern, where the regular shape of each hexagon is adapted to meet traffic requirements in that area. However, they presented their methods as a single site selection stage and did not go to validate their results by using a more detailed model. This work takes an alternative approach by considering the optimisation in two distinct steps: site selection and network configuration optimisation, which is similar to the real world network planning process. Useful techniques for the selection of the required number of sites should be considered, which motivates the investigation in Chapter 5. In Chapter 6 an investigation is undertaken to determine if effective site selections can be made as a precursor to network configuration optimisation with the aim of finding fixed and effective initial site selections from which further optimisations can be performed. After a specified time optimising the network it is possible to determine if the networks formed from less effective site selections can be significantly improved during optimisation and possibly surpass any initial advantage in making effective site selections.

2.4.5 NETWORK EVALUATION

Network evaluation is normally performed during the optimisation stage of automated cell planning to assess candidate network designs. In order to move from one network design to another to progress in the optimisation, each new network design needs to be evaluated and compared to the last evaluated network design to ascertain which design produces the most desirable cost function value.

Evaluation at this stage normally involves defining a cost function based on the performance of a network design for one distribution of mobile stations that have an associated traffic demand. When optimisation is complete the optimised network design can be evaluated using a static system simulator [22, 23, 24, 35, 78] to determine how robust the optimised network design is when dealing with different distribution and traffic demand scenarios.

Significant research has been produced for static system level simulations, but there appears to have been little consideration given to the use of more accurate traffic models as part of an optimisation cost function. This may be especially useful for planning UMTS networks due to the size of a cell being dependent on the traffic load at any moment in time and more accurate snapshot models may produce more effectively optimised cell plans. This idea motivates the work in Chapter 6.

2.5 SUMMARY

Many good models and solution techniques have been presented for cell planning and collectively consider a variety of problem scenarios. Literature concerning cell planning for UMTS has progressed in the last few years, but there is still potential for consideration and improvement of many aspects of cell planning.

Abstract models have been frequently applied, with the direct modelling approach being addressed from a linear programming point of view. The direct component based approach used by both Reininger *et al.* [74] and Hurley [42] has not yet been adapted and applied to UMTS networks, providing the motivation for network modelling in Chapter 3. A number of important aspects of UMTS have been highlighted and should be incorporated into the model.

The availability of easily accessible data sets is limited and careful consideration needs to be applied to modelling and generating data sets based on informed assumptions. This motivates the generation of network data sets and traffic modelling data presented in Chapter 3. The procedure for evaluating a network design is seldom explicitly stated by authors of cell planning papers. Research has rarely focused on static network evaluation. Traffic modelling should focus on incorporating UMTS services for a range of user density environments and methods for distribution should be considered in more detail for predicted data.

Capacity dimensioning has been less well-studied in comparison to coverage dimensioning and this provides the motivation for incorporating network dimensioning into the solution framework presented in Chapter 5. Previous work on network dimensioning has failed to explicitly specify the number of configured sites required to meet capacity specifications and the need for dimensioning techniques capable of considering both the uplink and downlink is highlighted. In Chapter 5 consideration is given to techniques that can help select sites from a candidate set in useful positions within the service area.

Network optimisation has often been the focus of cell planning. Many reviews and comparisons of techniques have been performed supporting the application of tabu search as part of the solution framework. Optimisation of a cell plan has previously involved evaluation for one snapshot of mobile stations. In Chapter 6 multiple snapshot evaluations as part of the cost function are considered. Differences in assumptions and models make benchmarking performance difficult to achieve. An alternative approach could involve finding lower bounds or an approximation of lower bounds on the number of required sites and making a comparison with the optimised solution. Finally, in Chapter 6, an investigation is undertaken to determine if effective site selections can be made as a precursor to optimisation.

CHAPTER 3

THE MODEL

To allow further investigation into automated cell planning, a means of modelling a cellular network is required. Two contributions are made in this chapter:

- the presentation of a network model extended from an existing GSM model for UMTS;
- the generation of three new data sets for demonstration and experimentation.

As highlighted by the discussion in Chapter 2, modelling a cellular network often presents a trade-off between computational simplicity and how closely the model approximates the real world. A decision has to be made early on as to where the developed model lies between these two extremes. However, irrespective of the granularity, there are common factors that need to be considered, such as:

- location information (normally involving a list of sites providing information concerning the geographical placement of sites);
- service information (concerning the specification of the service area that can be split into discrete points at which service quality thresholds are specified);
- propagation information (that can be estimated or measured involving the propagation loss of a signal between the transmitter and receiver);
- equipment configuration (involving the number of operational sites and the configuration of each antenna including selection of the type of antenna);

- traffic modelling (including specifications of traffic distributions, user density definitions and services specifications);
- evaluation metrics (such as capacity, coverage, revenue and quality of service).

The modelling approach employed in this thesis can be classified as a direct approach, involving the modelling of the relevant physical components of a cellular network with the subsequent application of newly developed network dimensioning and evaluation techniques for application within an optimisation framework. The model presented is a UMTS model drawing on ideas from the network model developed by Reininger, Dony, and Caminada [74]. The model developed in [74] was subsequently adapted and applied by Hurley [42] for GSM networks. The new model incorporates UMTS modelling aspects suggested by Holma and Toskala [41], and Laiho, Wacker, and Novosad [50]. The following sections present the model along with a number of assumptions and definitions that collectively form the modelling framework used in subsequent chapters. The lack of publicly available network data sets motivates the generation of three new UMTS network data sets that are utilised for experimentation and demonstration in the remainder of the thesis.

3.1 PROPAGATION MODEL

Propagation refers to the path travelled by a wave from one point to another through or along a medium. When travelling through free space a wave radiates spherically and the surface area of the wave increases with the square of the distance travelled, making the radiation pattern symmetric in all directions. For an ideal isotropic antenna transmitting with power P, the power received at distance D from the isotropic point would be

$$\frac{P}{4\pi D^2}$$

This is referred to as *propagation loss.*

As radio waves travel from a transmitting antenna to a receiving antenna, they suffer attenuation due to propagation loss. Realistically, signal strength measurements should be taken at all points in the service area, but this process is costly and time consuming due to the large amount of data required. As an alternative to measured propagation data, many mathematical propagation models have been developed and can be used to predict the received signal strengths expected at discrete points within the service area. One of the most frequently used models is the Okumura-Hata model which is based on measurements made by Y. Okumara [63] in Tokyo at frequencies up to 1920 MHz, which were used by M. Hata [37] to develop a mathematical model.

In the original model the path loss was computed by calculating an empirical attenuation correction factor for urban areas as a function of the distance between the site and mobile station, and the frequency. This factor was then added to the free space loss. The resulting value was corrected by factors accounting for antenna height and mobile station height. The following formula is used to calculate the propagation loss from each geographical site location to each test point in the service area:

$$Q = 137.4 + 35.2 \log_{10}(H)$$

where Q denotes the path loss measured in dB and H denotes the range in km.

Later correction factors were added to the model for street orientation, suburban, open areas and irregular terrain. The propagation loss data for each representative network is calculated by use of an existing scenario generator tool [83], that assumes the suburban correction factor of 8dB. Hence the equation is corrected to

$$Q = 129.4 + 35.2 \log_{10}(H) \tag{3.1}$$

Equation 3.1 is used to calculate propagation values for suburban, urban and rural scenarios considered in this work.

3.2 NETWORK MODEL

A service area, M, is modelled as a grid or mesh and all points located within M are defined by their Cartesian coordinates. Points on that grid at which propagation and service information is available are known as service test points (STPs), the set of which is defined $T = \{t_1, ..., t_{n_T}\}$.

A *network*, $N = \{s_1, s_2, \ldots, s_{n_{sp}^o}\}$ is defined as a subset of sites selected from S the set of all *candidate* sites. These are the sites that are *operational*. Each site in S has either a single omnidirectional antenna or has several *co-sited* directional antenna. n_{op} denotes the total number of antennae in the network. Each antenna, A_k, has variables associated with it which determine its *configuration* and include:

- Number of antennae;
- Transmission power (denoted $P^{A_k} \in \{27, 28, 29, ...50\}$ in dBm);
- Tilt, β, of each antenna (denoted $A_k^\beta \in \{0, -1, -2, ..., -15\}$ where -15 is the maximum available down-tilt);
- Azimuth, δ, of each antenna (denoted $A_k^\delta \in \{1, 2, 3, ..., 360\}$ in degrees).

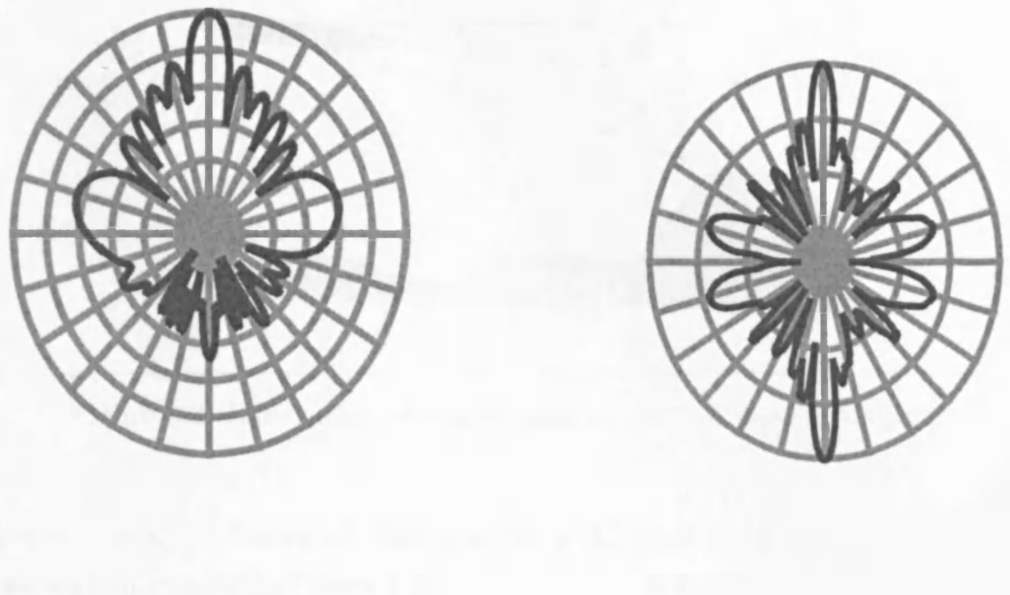
The radiation pattern of an antenna is characterized by two functions that define the horizontal and vertical losses, in dBi, and is dependent on the horizontal and vertical angles of the antenna relative to the STP and site. For a given antenna type:

- $L_v^{A_k}$ is a loss, in dBi, determined by the vertical radiation pattern of A_k. Figure 3.1 illustrates the vertical radiation pattern of a directional and an omnidirectional antenna;
- $L_h^{A_k}$ is a loss, in dBi, determined by the horizontal radiation pattern of A_k. Figure 3.2 illustrates the horizontal radiation patterns of a directional and an omnidirectional antenna.

The vertical radiant loss $L_v^{A_k}$ of an antenna A_k to an STP is calculated from two angles:

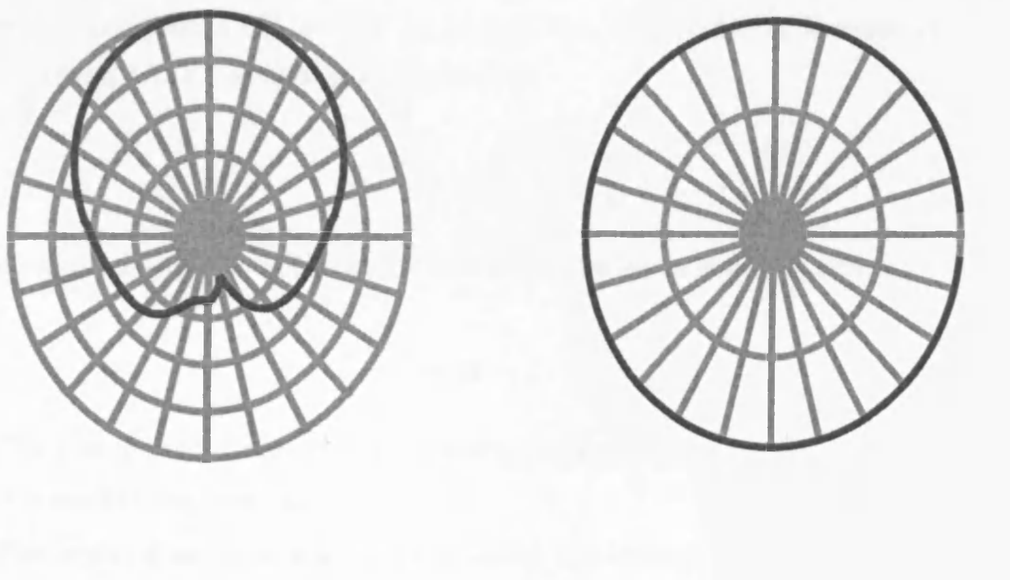
- the vertical angle of incidence denoted γ;
- the antenna tilt denoted A_k^β.

The angle of incidence, γ, gives the angle of the strongest path from a site to a STP. The required angle, θ, needs to take into account the antenna tilt and is



(a) Directional (b) Omnidirectional

Figure 3.1: Vertical radiation patterns illustrating the gain of each antenna.



(a) Directional (b) Omnidirectional

Figure 3.2: Horizontal radiation patterns illustrating the gain of each antenna.

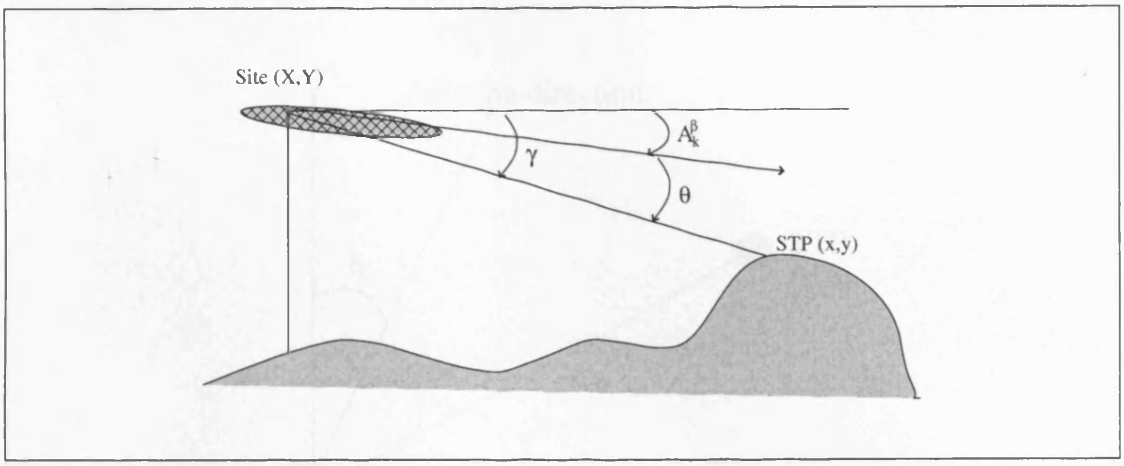


Figure 3.3: Illustration of angles used in vertical loss calculation.

therefore the angle measured clockwise from A_k^β to γ as shown by the equation below and illustrated in Figure 3.3.

$$\theta = (A_k^\beta - \gamma) \bmod 360 \tag{3.2}$$

The horizontal radiant loss, $L_h^{A_k}$, of an antenna, A_k, is calculated from the horizontal angle between an STP, ϵ, and the antenna azimuth, A_k^δ. This calculation uses the coordinates of the STP (x, y) and the coordinates of the site supporting the antenna (X, Y) as shown in Figure 3.4.

$$\epsilon' = \arctan\left(\frac{y - Y}{x - X}\right) \tag{3.3}$$

The required angle, ϵ, is the angle from δ clockwise to ϵ' and is defined

$$\epsilon \equiv (90 - \epsilon' - A_k^\delta) \tag{3.4}$$

The loss is then determined by finding the angle in a lookup table and reading the corresponding loss value.

The type of antenna selected will affect the strength of the transmitted and received signals; each antenna can be subject to an associated *transmission gain*, G_k^A, and *transmission loss*, L_k^A.

The propagation loss from each antenna to each STP in the service area is given by Q where $Q_{(k,i)}$ is the propagation loss, measured in dB, between A_k (the

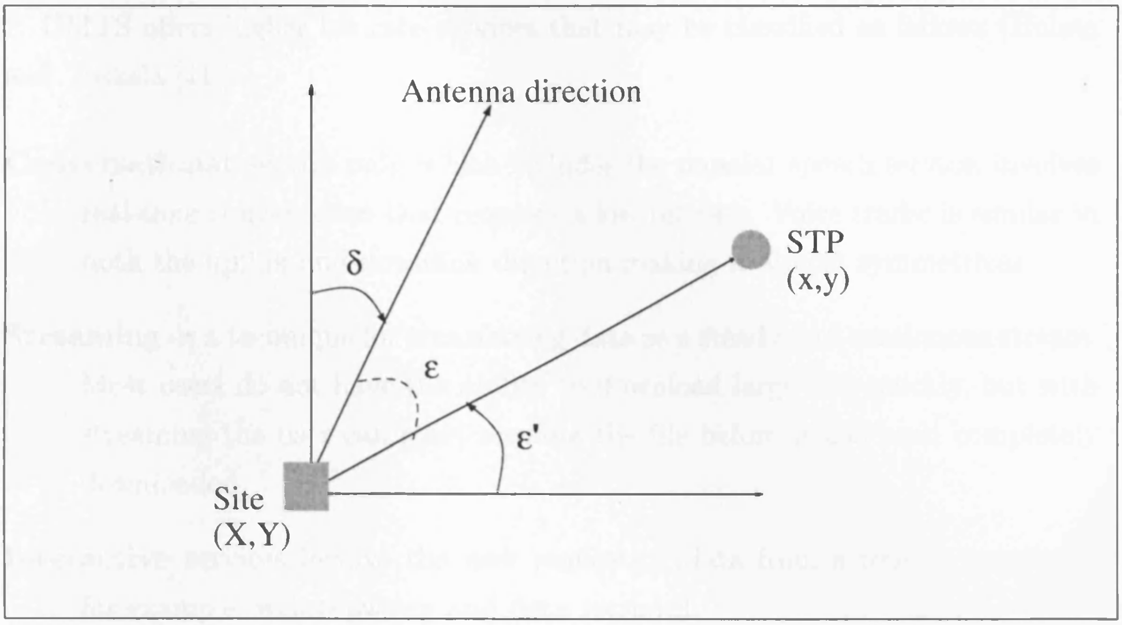


Figure 3.4: Horizontal loss angle

antenna) and t_i (the STP). Conversely $Q_{(i,k)}$ denotes the propagation loss from t_i to s_k. In this model it is assumed that $Q_{(k,i)}$ and $Q_{(i,k)}$ are equivalent and are generated using the Okumara-Hata propagation loss model.

3.3 Service and traffic

A STP is said to be *covered* if at least one antenna provides sufficient power for the required service threshold to be met. A network provides a service based upon criteria defined by the network operator and must satisfy the capacity or traffic requirements in an efficient manner. Each *user* or *subscriber* is located at a STP and uses a *mobile station* to communicate with the cellular network. Users are distributed across the service area according to a certain *user density* and distribution *e.g.* 30 users per square kilometre distributed randomly.

A mobile station, u_j, has the capability to transmit and receive voice and data calls and is located at a STP. Each mobile station has an associated and fixed reception gain and loss, in dB, represented by

- l_j is the loss experienced at u_j.
- g_j is the gain experienced at u_j.

UMTS offers higher bit rate services that may be classified as follows (Holma and Toskala [41]):

Conversational service only, which includes the popular speech service, involves real-time conversation that requires a low bit-rate. Voice traffic is similar in both the uplink and downlink direction making it almost symmetrical.

Streaming is a technique for transferring data as a steady and continuous stream. Most users do not have the ability to download large files quickly, but with streaming the user can start viewing the file before it has been completely downloaded.

Interactive services involve the user requesting data from a remote computer, for example, web browsing and data retrieval.

Background services consist of data traffic for applications like email and SMS that can be delivered in the background as they are not delay sensitive.

These four classifications were characterised by the UK's Radiocommunications Agency (RA) [4] as eighteen separate services, whilst the UMTS Forum [1] outlined six different types of service that are considered in this work and are listed along with their corresponding bit rate in Table 3.1.

When considering a UMTS network, it is unlikely that the type of traffic (*i.e.* service type) will be homogeneous. As a result a *service mix* must be defined that represents the heterogeneity of traffic by the proportion of simultaneously active users that utilise each service. It is worth noting that not all service types have to be utilised at once. Given a user density, u_d, the number of mobile stations for distribution in the service area is determined as follows

Service Type	Bit Rate [kbps]
High Rate Interactive Multimedia	128.0
High Rate Multimedia	2000.0
Medium Rate Multimedia	384.0
Switched Data	14.4
Simple Messaging	14.4
Speech	16.0

Table 3.1: UMTS Forum service types.

$$n_u(M) = u_d \times M \text{ in square km}$$

This allows the number of simultaneously active users utilising a service to be determined by

$$n_u(f) = \kappa(f) \times n_u(M)$$

where $\kappa(f)$ denotes the proportion of simultaneously active users utilising f.

For example consider a scenario with 100 mobile station users, where the proportion of simultaneously active users is set at 0.5. Assume there are 90% of simultaneously active users that require a voice only service at 16kbps and 10% whom require multimedia service at 384kbps. That gives 45 simultaneously active users utilising a voice only service with total bit rate of 720 kbps and 5 simultaneously active users utilising a multimedia service with a total bit rate of 1920 kbps. The representative traffic scenarios used for experimentation purposes are defined in Section 3.8.

3.4 DOWNLINK PILOT SIGNAL COVERAGE

When an antenna transmits a signal to a receiving mobile station, the direction of communication is referred to as the *downlink* (or less frequently the *forward link*). The transmitted signal will be received by many different mobile stations in the service area and at varying levels of signal strength. The signal received at the mobile station will have been attenuated by aspects such as propagation loss, gains and losses of the antenna and mobile station receiver gains and losses. The following equation models the signal received at a STP, t_i, having been transmitted from an antenna, A_k,

$$P_k^r(i) = P^{A_k} + G_k^A - L_k^A - Q_{(k,i)} - L_v^{A_k} - L_h^{A_k} - l_j + g_j \text{ dBm} \qquad (3.5)$$

Figure 3.5 provides an example of signals received at a particular STP.

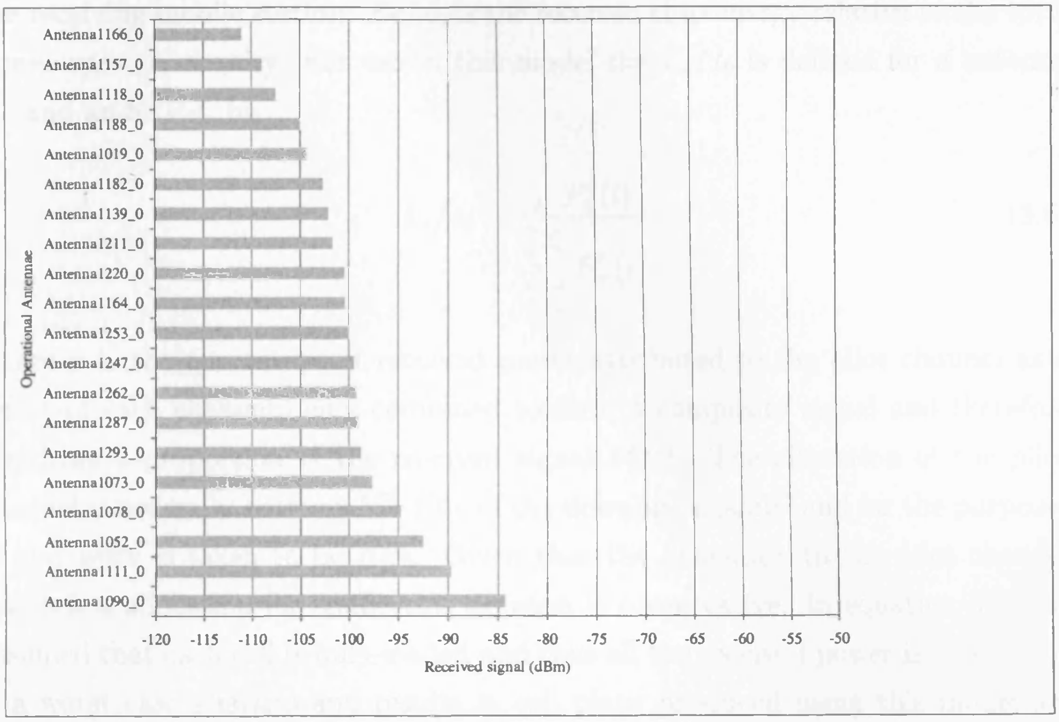


Figure 3.5: This bar chart provides an example of all signals received at a particular STP

The downlink signal consists of a number of channels* including a pilot channel, synchronization channel, several paging channels and several traffic channels [41, 93]. However, it is the pilot and traffic channels that are of primary interest when cell planning. The pilot channel is of particular interest as it is transmitted continuously by each antenna and is subsequently used to determine the coverage area of the antenna's cell in the network which is fundamental to cell planning. For example when the power allocated to the pilot channel is increased the cell area is likely to expand and conversely when the power of the pilot channel decreases the cell area will most likely shrink. It is important that each mobile station is able to receive a suitable strength pilot signal that is above an operator defined threshold to allow a call to be made successfully. Therefore obtaining and maintaining good pilot signal coverage is very important to operators.

Specifically the measurement of the signal to noise ratio, E_c/I_0, of the pilot channel gives an indication of which antenna provides the most suitable signal to

*These are combined to form a composite signal to be transmitted in the downlink.

the receiving mobile station. Ec/I_0 is the received chip energy relative to the total power spectral density. For use in this model the E_c/I_0 is defined for a antenna A_k and an STP t_i by

$$E_c/I_0 = \frac{\mu \; P_k^r(i)}{\sum_{m=1}^{n_{op}} P_m^r(i)} \tag{3.6}$$

where μ is the percentage of received power attributed to the pilot channel as a result of each channel being combined to form a composite signal and therefore acquiring a proportion of the received signal $P_k^r(i)$. The allocation of the pilot channel is normally between 5%-10% of the downlink channel and for the purposes of this work is taken to be 10%. Given that the allocation to the pilot channel leaves less allocation for traffic this decision is conservative. In equation 3.6 it is assumed that each cell is fully loaded and thus all the received power is used. This is a worst case scenario and results in cell plans produced using this model are conservative.

Ec/Io is calculated at the downlink between each STP and operational antenna, which allows the best serving antenna or *best server*, at each STP, to be determined. The best server is defined as the antenna that provides an STP with the highest E_c/I_0 signal assuming the required coverage threshold is met, for example, the E_c/I_0 must be stronger than -18dB. A antenna's signal coverage area can then be determined and is known as a *cell*. Hence a set of cells is denoted

$$C = \{c_1, c_2, \ldots, c_{n_{op}}\}$$

where $c_k \in C$ is made up of STP that have b_k as the strongest server. The number of mobile station users in cell c_k is denoted $n_u(c_k)$. Figure 3.6 provides an example illustration of the E_c/I_o signals received at a particular STP within the service area for a network containing 20 operational sites each having an associated omnidirectional antenna.

In UMTS an *active set* of antennas is held for each STP in the service area. Antennae belonging to the active set are required to transmit a signal that exceeds a specified active set threshold. In Figure 3.6 the threshold for obtaining a pilot signal is set at -18dB, making Antenna1090_0 the best server. An active set of size

3 is used, with an active set threshold of −20dB, thus containing Antenna1090_0, Antenna1111_1 and Antenna1052_0. Determination of the active set allows a antenna to *handover* a signal to another antenna. Although this capability has been built into the model and is a significant issue for traffic coverage in UMTS, experimentation for handover is not undertaken and further details of the handover process and different types of handover are not included.

This model differs from a pure highest signal model as interference is considered in the E_c/I_0 calculation, which is used to determine the cell coverage area. In a highest signal model the cell coverage area is determined by the strongest signal received at each STP without considering interference.

Figure 3.7 can be produced to illustrate the best server allocation per STP in the service area. This type of illustration is often referred to as a cell plan or network design. Each best serving antenna is allocated a colour and when a STP has a particular antenna as the best server it is allocated the colour of that best serving antenna, effectively highlighting each cell in the network.

3.5 UPLINK COVERAGE

When a mobile station transmits a signal to a receiving antenna, the direction of communication is referred to as the *uplink* or less frequently the *reverse link*. In a WCDMA system the downlink and the uplink have different link structures and are not symmetric. The uplink consists of two types of logical channels: access and traffic channels. The reason a pilot channel is not used on the uplink is because it would be impractical for each mobile station to transmit its own pilot sequence. It is assumed that if the mobile receives pilot power, then there is sufficient power at the mobile and transmitting antenna for traffic coverage to occur (*i.e.* required E_b/N_o ratio can be attained on the uplink and downlink). Although in practice this may not be true, modelling such traffic results in conservative cell loads.

Power control ensures that each user in the network receives and transmits just enough energy to convey information while causing minimal interference to other users. When a mobile station initiates a call it adjusts its transmission power based on the received pilot signal. This provides an approximate measure of the propagation loss between the mobile station and the site. The stronger the received pilot signal the less initial transmission power is needed by the mobile station. In this work it is assumed that each mobile station is transmitting at the most suitable power setting available and thus power control is not specifically modelled.

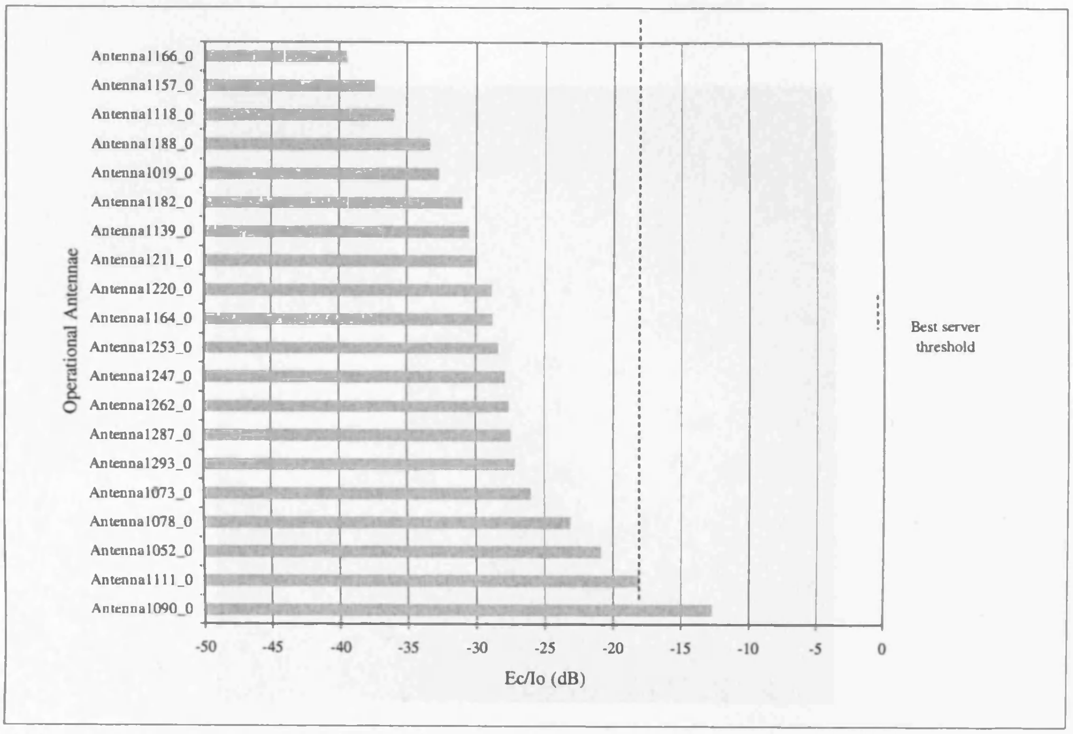


Figure 3.6: An example of received pilot signals at a STP in the service area

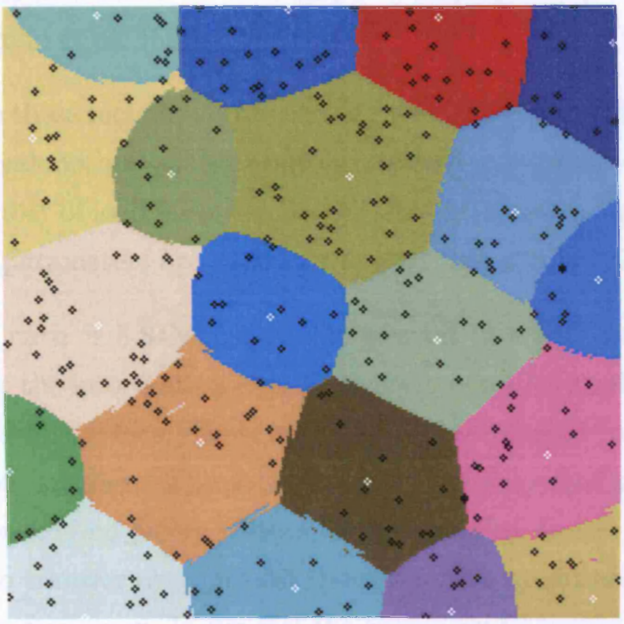


Figure 3.7: Illustration of best server at each STP

3.6 LOAD FACTOR CALCULATIONS

When the pilot signal has been received and the best server determined, *load factor* calculations can be performed for each cell and the total network load found. The load factor is concerned with estimating the amount of supported traffic per cell compared to the theoretical maximum. In general there are two different methods for modelling the downlink and uplink load in a UMTS network model:

- wide-band received power (Shapira [76] and Shapira and Padovani [77]);
- estimation of load based on throughput (Allen et al. [7], Holma and Toskala [41], and Laiho et al. [50]).

Although both these techniques are equally valid, the model of this thesis adopts the throughput load method as this approach is used in a lower bounding technique from which a number of load factor equations are extracted and applied in Chapter 4. The following parameters are used in the load factor equations:

WCDMA chip rate is 3.84Mcps. A chip is a bit in a code word, which is used to modulate the information signal. Every second 3.84 million chips are sent over the radio interface. However, the number of data bits that are passed over is much smaller. The ratio between the chip rate and the *bit rate* is called the *spreading factor.* Assuming a spreading factor of 1.0 would allow each chip to transfer one data bit, however, this would prevent another user utilising the frequency. In general the spreading factor determines how large a proportion of bandwidth a user can have. The sequence of chips used to modulate the data bits is called the *spreading code.* Each user is allocated a unique spreading code.

Orthogonal codes are used in the downlink to help distinguish between users. Assuming there is no multi-path propagation orthogonality exists when the antenna's signal is received by the user's mobile station. The orthogonality factor is therefore 1.0 for perfectly orthogonal users. However, if there is sufficient delay spread in the radio channel, the mobile station will experience part of the antenna's signal as interference. Realistically the orthogonality is between 0.4 and 0.9 as channels are typically affected by multi-path propagation.

E_b/N_0 measure is defined as the signal energy per bit (E_b) divided by noise spectral density (N_0), and is required to meet a pre-defined quality of service. It is measured at the input to the receiver and is used as a measure of signal strength. Since there is no pilot channel in the uplink, the measure that needs to be considered is the E_b/N_0 of the uplink traffic channel. The link E_b/N_0 translates directly into bit error rate, which has implications on uplink quality. Making sure that the link supports an adequate E_b/N_0 ensures the quality of the link. The aim of power control in WCDMA is to keep the received E_b/N_0 constant. The average transmit powers of the mobile stations to each antenna are estimated so that they fulfil the required E_b/N_0. In this work it is assumed that the power transmitted by each mobile station is the amount required to meet the target E_b/N_0. As a result actual E_b/N_0 calculations are not made in this model, instead target E_b/N_0 values are used and specified as an input to the model. This assumption follows from Nokia's approach specified in [41]. The target E_b/N_0 values are based on the typical values for each service.

Activity factor of a user can be defined as the percentage of time that a signal is present in the channel in either direction for a specified time interval *i.e.* busy hour. For example voice traffic typically has an activity factor of 0.67, whilst data traffic has an activity factor of 1.

Interference can be defined as the overlapping or collision of two or more signals and is split into two categories in a UMTS network: *intra-cell* and *inter-cell* interference. Interference that comes from the same cell is called intra-cell interference, whilst interference from adjacent cells is called inter-cell interference. In GSM systems, interference is managed by channel assignment. However, in systems using WCDMA all users share the same channel and each user's signal appears to the other users as interference resulting in mobile station users affecting each other's ability to transmit and receive signals. In the uplink the interference affects all connections of one cell similarly. In the downlink the interference experienced at each mobile station is highly dependent on the users location and is therefore different for each mobile station user.

3.6.1 THROUGHPUT BASED DOWNLINK LOAD CALCULATION

Throughput based downlink load estimation can be calculated by using the sum of the downlink allocated bit rates weighted by the E_b/N_o values. Therefore, the downlink load of a cell, c_k, is defined*:

$$\eta_{DL}(c_k) = \sum_{j=1}^{n_u(c_k)} v_j \cdot \frac{(E_b/N_o)_j}{W/R_j} \cdot \left[(1-\alpha_j) + I_j^{DL}\right] \tag{3.7}$$

where

- v_j is the activity factor of mobile station user j and is dependent on the service;
- E_b/N_{o_j} is the signal energy per bit divided by noise spectral density required to meet a predefined quality of service that is expected by user u_j;
- W is the WCDMA chip rate set at 3.84 Mcps;
- R_j is the bit rate of user u_j and is dependent on the service;
- α_j is the orthogonality factor of the channel dependent on multi-path propagation;
- I_j^{DL} is the other cell to own cell interference ratio defined:

$$I_j^{DL} = \frac{\sum_{q=1,q\neq k}^{n_{op}} P_q^r(j)}{P_k^r(j)} \tag{3.8}$$

Each user has a different I_j^{DL} dependent on location in the cell.

3.6.2 THROUGHPUT BASED UPLINK LOAD CALCULATION

The uplink load factor of a cell c_k is defined:

*Notation here and in section 3.6.2 is consistent with that used in the corresponding load factor equations in 3GSTART [7] and by Holma and Toskala [41].

$$\eta_{UL}(c_k) = (1 + I^{UL}) \sum_{j=1}^{n_u(c_k)} \left(1 + \frac{W}{r_j \cdot v_j \cdot (E_b/N_o)}\right)^{-1} \tag{3.9}$$

where r_j is the uplink bit-rate of user j (and is dependent on the service) and the interference experienced in the uplink, $I^{UL}(c_k)$, is defined

$$I^{UL}(c_k) = \frac{\sum_{q=1, q\neq k}^{n_{op}} \sum_{j=1}^{n_u(c_q)} P_k^r(j)}{\sum_{j=1}^{n_u(c_k)} P_k^r(j)} \tag{3.10}$$

The results in Table 3.2 can be produced through application of equation 3.7 (downlink load factor) and equation 3.9 (uplink load factor). The parameters used in these equations have typical values as used in 3GStart [7].

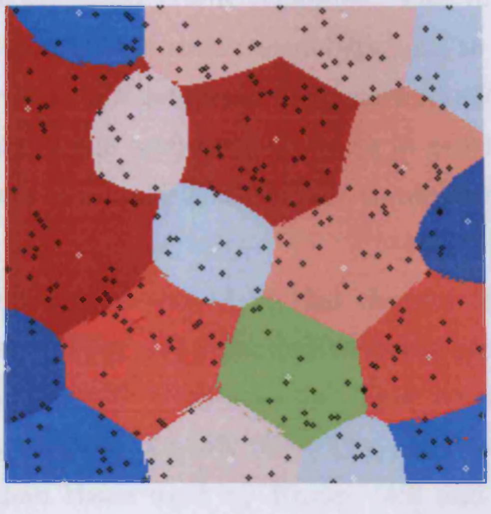
Desired cells have loads that meet a specified load target by falling between pre-defined loading bounds. In this model the target cell load, d, is 0.6 in the uplink and downlink (although the model is capable of accepting different target loads in uplink and downlink). A margin, m, is permitted either side of d and for this model is taken to be 10%. Both the target cell load and margin also have typical values as used in 3GStart [7]; these parameters result in a lower target bound of a cell is 0.54 and the upper target bound is 0.66. Any cell load that falls within the lower and upper bound is deemed desired. For example in Table 3.2 Antenna1211_0 meets the target uplink cell load as its uplink load, $\eta_{UL}(c_k)$ = 0.6063, falls within the target load bounds. *Over-loaded* cells are defined as having loads above the specified cell target plus allowed margin and *under-loaded* cells have loads below the specified target less the allowed margin.

Each cell load obtained can also be compared to the theoretical maximum capacity of an individual cell in the WCDMA network called the pole capacity. When a cells load approaches 1.0 the corresponding noise rise approaches infinity resulting in the cell load reaching its pole capacity.

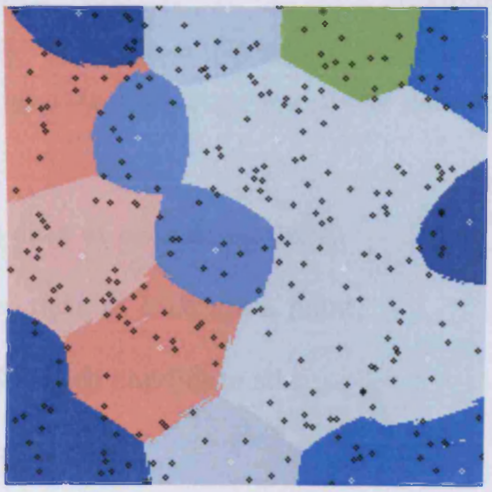
The pilot cell plan shown in Figure 3.7 can be adapted to display cell load. Instead of colouring each cell, according to best server, the cells are shaded by load as shown in Figure 7.11. Over-loaded cells appear graduated red to white, under-loaded cells appear graduated blue to white and desired cells are green.

	P^{A_k}	A_k^δ	A_k^β	A_k	STP	$n_u(c_k)$	$\eta_{UL}(c_k)$	$\eta_{UL}(c_k)$ state	$\eta_{UL}(c_k)$	$\eta_{UL}(c_k)$ state
Antenna1052_0	40	0	0	Omni	1221	6	0.7212	Over	0.2973	Under
Antenna1247_0	40	0	0	Omni	520	3	0.2715	Under	0.1227	Under
Antenna1182_0	40	0	0	Omni	4724	23	1.153	Over	0.6961	Over
Antenna1019_0	40	0	0	Omni	1420	9	0.7796	Over	0.2413	Under
Antenna1211_0	40	0	0	Omni	3395	19	1.7912	Over	0.6064	Desired
Antenna1118_0	40	0	0	Omni	1600	4	0.5049	Under	0.9725	Over
Antenna1111_0	40	0	0	Omni	4605	18	1.5803	Over	1.0226	Over
Antenna1078_0	40	0	0	Omni	2116	11	0.7392	Over	0.3618	Under
Antenna1188_0	40	0	0	Omni	1080	3	0.2330	Under	0.2237	Under
Antenna1262_0	40	0	0	Omni	1311	4	0.5341	Under	0.8960	Over
Antenna1164_0	40	0	0	Omni	2550	8	0.5254	Under	0.4391	Under
Antenna1139_0	40	0	0	Omni	8311	39	1.7755	Over	1.0803	Over
Antenna1220_0	40	0	0	Omni	2083	12	1.3388	Over	0.6842	Over
Antenna1293_0	40	0	0	Omni	4317	25	4.7686	Over	1.1744	Over
Antenna1166_0	40	0	0	Omni	1121	9	0.4916	Under	0.1947	Under
Antenna1253_0	40	0	0	Omni	3958	13	1.3920	Over	0.7643	Over
Antenna1287_0	40	0	0	Omni	1117	3	0.1425	Under	0.1011	Under
Antenna1157_0	40	0	0	Omni	866	0	0	Under	0	Under
Antenna1073_0	40	0	0	Omni	1973	9	0.8285	Over	0.4483	Under
Antenna1090_0	40	0	0	Omni	6930	27	2.1112	Over	0.8043	Over

Table 3.2: Uplink and downlink cell load result



(a) Uplink load



(b) Downlink load

Figure 3.8: Cell plans shaded by load.

3.7 REPRESENTATIVE NETWORK SCENARIOS

As discussed in Chapter 2 network data sets are in short supply within the public domain, with operators tending to keep confidential their network configuration data and measured or predicted traffic scenarios. This hinders research into automated cell planning and means that researchers have to develop their own data sets or use available legacy data sets from GSM networks for UMTS network planning. As a result many of the assumptions made in generating the data sets are not detailed in the literature making it difficult to understand what authors have assumed.

Three new data sets are presented in this chapter for experimentation and demonstration purposes. They are regarded as being representative as they are competitively dimensioned with data sets that have been developed and experimented with by other authors [42, 55, 86]. The data sets presented consider a smaller service area than those used by Hurley [42] and Vasquez and Hao [86]. However, service, propagation and site data are provided per 30 metres and 45 metres of the service area, compared to the data provided per 200 metres of the service area by [42, 86]. This makes the number of points that form the grid approximately equal for all data sets. For each of the data sets the following classes of data are required:

(a) propagation loss data at each mesh point;

(b) angle of incidence data at each mesh point;

(c) location details for each candidate site;

(d) configuration parameters;

(e) service thresholds and traffic data.

As previously highlighted in Section 3.1 the propagation loss and angle of incidence data are generated using a scenario generator tool [83]. This tool also produces a set of a specified number of candidate sites. External to the tool, an antenna file is generated and can be input to the model and within the model antennae can be initially configured with an omnidirectional or directional antennas. As mentioned in Section 3.3, UMTS Forum services are incorporated in the model. Three differently sized data set scenarios are presented and are referred to as KORNET1, KORNET2 and KORNET3 for the remainder of this work.

The KORNET1 data set contains a service area of 7km by 7km. The service area is square and is comprised of 55,225 test points, that is 235 by 235, with an interval of 30 metres between each test point. At each test point propagation and angle of incidence data are calculated. The candidate site set contains 300 potential sites available for deployment and configuration, the locations of which are shown in Figure 3.9. KORNET3 has the same service area dimensions as KORNET1 with a reduced candidate site set of 200 locations as illustrated in Figure 3.11. This data set is used once in this work for comparison purposes. The KORNET2 data set contains a service area of 10km by 10km with the same number of test points as KORNET1, however the interval between each test point is increased to 45 metres. There are 700 candidate sites available for deployment, which are illustrated in Figure 3.10. Table 3.3 provides a summary of the three data sets.

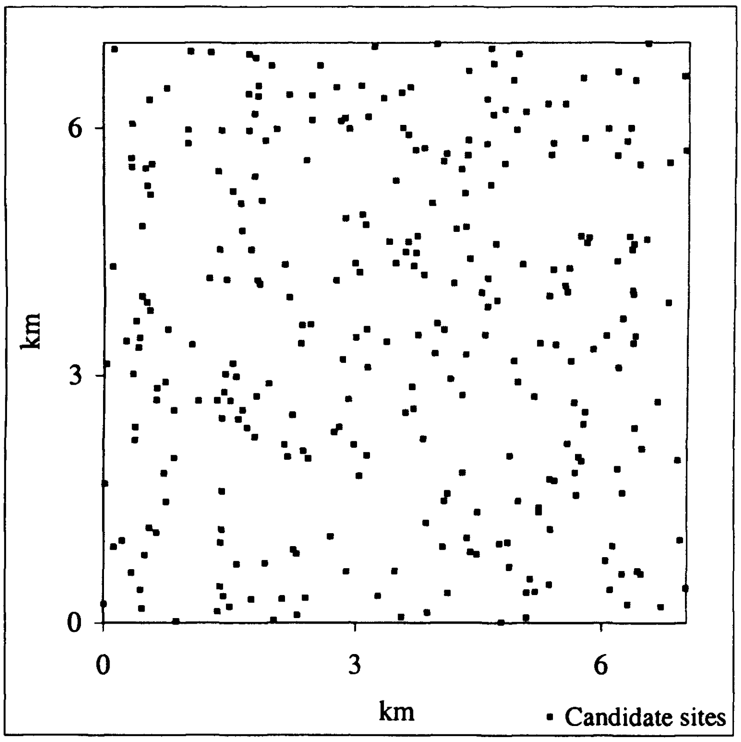


Figure 3.9: KORNET1 data set with 300 candidate sites.

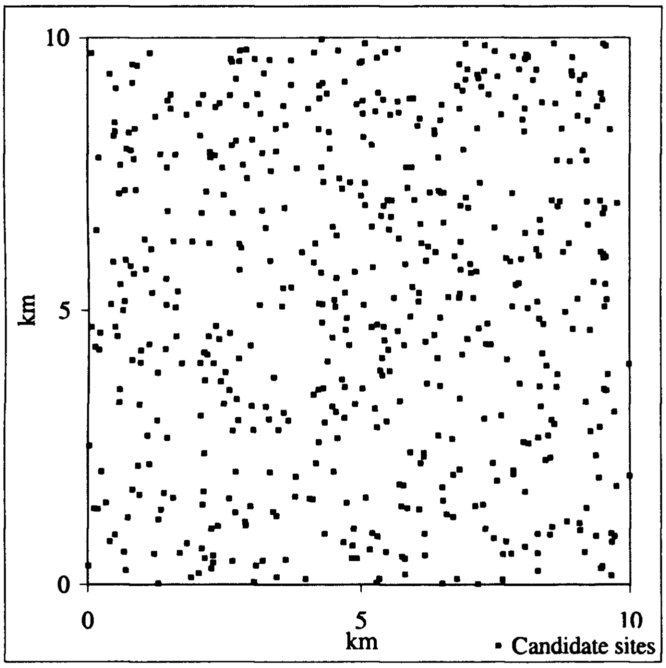


Figure 3.10: KORNET2 data set with 700 candidate sites.

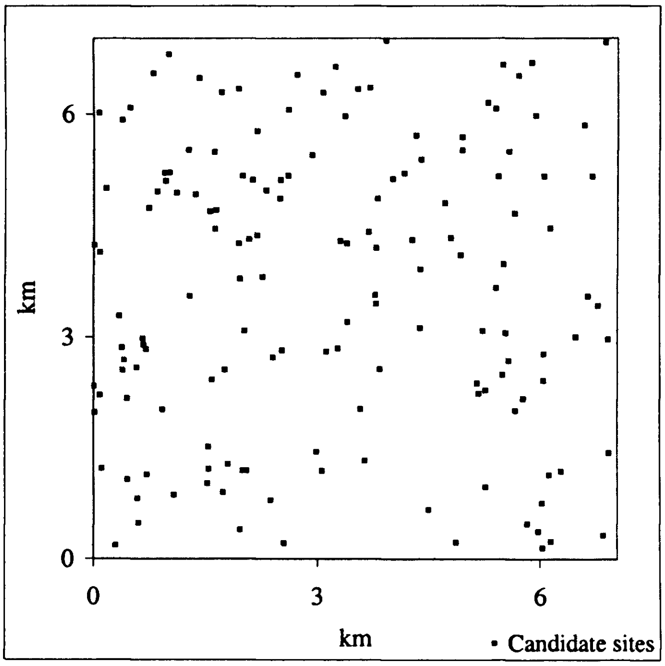


Figure 3.11: KORNET3 data set with 150 candidate sites.

Scenario	Service Area	Interval	Candidate sites	Illustration
KORNET1	7km by 7km	30m	300	Figure 3.9
KORNET2	10km by 10km	45m	700	Figure 3.10
KORNET3	7km by 7km	30m	150	Figure 3.11

Table 3.3: Summary of KORNET1, KORNET2 and KORNET3 data sets. Okumara-Hata propagation model is used to generate propagation information in each data set.

3.8 REPRESENTATIVE TRAFFIC SCENARIOS

Public access to measured or predicted data sets gathered by operators is limited and was not available for use in this thesis. Instead, new traffic data has been generated based on a number of informed assumptions for traffic density, distribution and service mix.

Population density statistics are taken from work completed by Bichot *et al.* [13] who give the population density for three addressable markets: rural, suburban and urban, similar to work carried out by Cavdar and Akcay [19]. In light of this report the user densities shown in Table 3.4 are used for experimentation purposes.

Statistics for the number of simultaneously active users expected to require service from a UMTS network at peak time are supplied by the UMTS Forum in their report entitled '3G offered traffic characteristics' [26]. The mobile traffic forecasts in the report are built on extensive market analysis of 3G service opportunities in a representative European country. In the report it is stated that the maximum third generation penetration is 90% of the country's population and from this the mobile station user density used for experimentation is determined (column 4 3.4). The report also states the number of simultaneously active mobile station users at peak time will be approximately 10% of the population user density after the 3G market penetration correction has been made.

This work considers a mix of services combining voice and multimedia traffic as introduced in Chapter 3. Laiho, Wacker, and Novosad [50] state that traffic density differs between services *e.g.* in a particular service area there may be significantly more voice users than multimedia users; as such this should be incorporated in the traffic model. Laiho, Wacker, and Novosad [50] suggest using one user density for

Market	Population density inhabitants per square km	Population density used in tests inhabitants per square km	Subscriber density after 90% market penetration u_d	Proportion of sim. active users $\kappa(M)$	Number of sim. active users
Rural	< 100	55	50	0.1	5
Suburban	100 to 500	280	250	0.1	25
Urban	> 500	500	450	0.1	45

Table 3.4: 3G market penetration for a European country. Population density statistics are taken from work completed by Bichot *et al.* [13] who give the population density for three addressable markets: rural, suburban and urban

a service area with heterogeneous traffic requirements and from this the number of simultaneously active users that require each service can be stated as a proportion of the overall density; this assumption is also used for traffic modelling in this thesis.

Evaluation of a network is reliant on the current geographic distribution of mobile stations within the service area. Dehghan *et al.* [22] defined a distribution where each mobile station in the distribution has a traffic demand which is dependent on the service required by the mobile station user, as a traffic *snapshot*; this definition is frequently used in the subsequent chapters. When measured data are used for traffic modelling, the distribution is already provided and is obviously realistic. However, due to the lack of measured traffic data sets it is necessary to be able to produce reasonable traffic snapshots. Thus for predicted traffic data, mobile station distributions can be generated based on statistical distributions or realistic models. The following sections present a number of techniques used for mobile station distribution in this work, referred to as: *uniformly random*, *random-with-cluster* and *shared-load.*

3.8.1 UNIFORMLY RANDOM

A uniformly random distribution is a popular choice for mobile station distribution in the related literature (*e.g.* [18]). An example of this type of mobile station placement can be seen in Figure 3.12. Each mobile station can then be placed at a uniformly random STP within the service area. Only one mobile station can be located at an STP and each mobile station manages its own traffic demand, making this technique representative of a real traffic scenario. The random number generation used throughout is performed using a pseudo-random number generator, which allows uniformly random numbers to be generated from two recorded seeds.

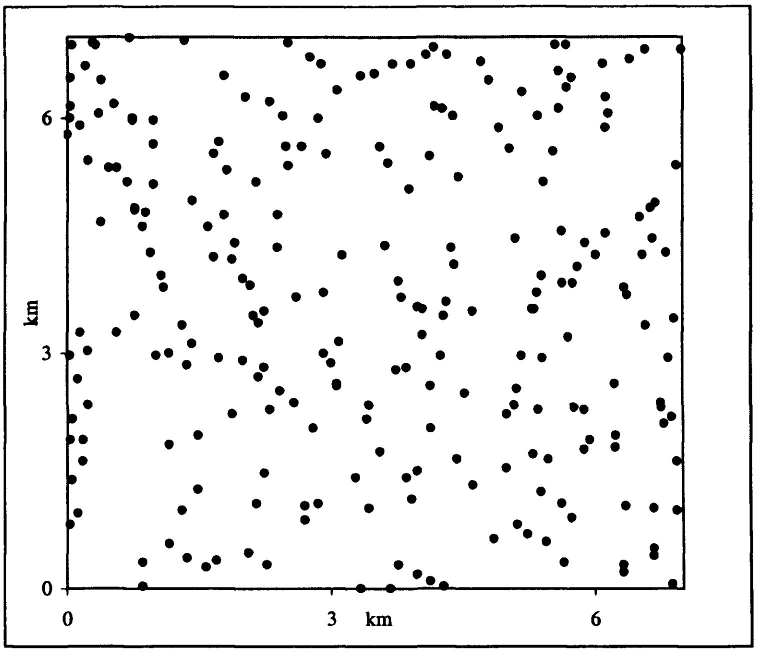


Figure 3.12: A uniformly random distribution of mobile stations

3.8.2 RANDOM-WITH-CLUSTER

Random-with-cluster distribution is presented with the aim of introducing traffic clusters into a random traffic distribution. The cluster in this distribution aims to represent the operational situation experienced in towns and villages when the traffic demand is likely to be higher. An example of this mobile station distribution can be seen in Figure 3.13. Where 50% of mobile stations are distributed uniformly across the service area and 50% form a cluster.

As in the previous method the set of mobile station users is generated and a percentage of these mobile stations are uniformly randomly distributed across the service area. For experimentation purposes 50% of mobile stations are distributed randomly, although this percentage can be varied. A random point (x,y) is then selected to be the origin of the mobile station cluster. In order to produce a point

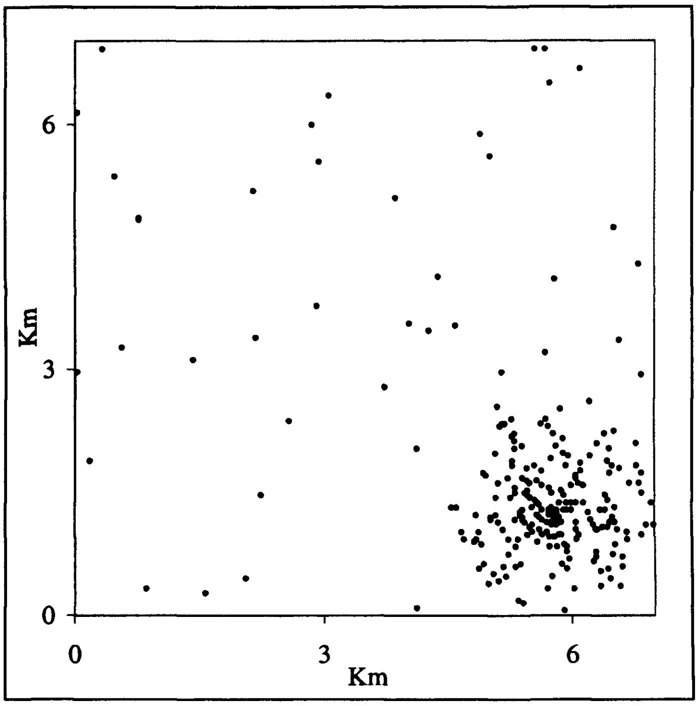


Figure 3.13: Random-with-cluster distribution

within the cluster region two parameters are introduced: **maxRadius** and **maxAngle**, where **maxRadius** denotes the required radius of the cluster and **maxAngle** defines the arc length of the cluster. Hence, a point in the cluster can be found by use of the following equations

$$x = \mathrm{r} \times \cos(\theta) \tag{3.11}$$

$$y = \mathrm{r} \times \sin(\theta) \tag{3.12}$$

where r is generated randomly within the range $[0, \theta_{\max}]$ and θ is in the range $[0,$ **maxAngle**$)$. The generated point (x, y) is then translated by (X, Y), which assumes an origin at $(0, 0)$ is then translated to the point (x, y) located at the centre of the cluster. That is, users are uniformly random with a higher density of users within the cluster.

3.8.3 SHARED-LOAD DISTRIBUTION

In UMTS networks, coverage and capacity cannot be considered separately. With the use of WCDMA technology in UMTS, the coverage size of a cell is dependent on the traffic load, which results in a process called *cell breathing.* Shared-load distribution is a new distribution that aims to share the traffic demand equally across all STPs in the service area. Although this technique is not a realistic representation of an operational traffic scenario, the aim is to create a distribution which closely links the coverage and the capacity of a cell. This technique that requires the total network demand, *i.e.* uplink bit-rate and downlink bit-rate for each service, to be calculated and distributed equally across the service area. Firstly the total bit-rate is calculated for each service for downlink, $R(N)$, and uplink, $r(N)$, as follows:

$$\text{total } R(N) = \sum_{f=1}^{n_f} n_u(f) \times R(f) \tag{3.13}$$

$$\text{total } r(N) = \sum_{f=1}^{n_f} n_u(f) \times r(f) \tag{3.14}$$

A mobile station can be placed at each STP in the service area and this idea of locating a virtual mobile station as each STP is similar to an approach for sharing transmitter powers across the service area as used by Dziong, Krishnan, Kumar, and Nanda [23]. Each mobile station is given traffic demand values as demonstrated by equation 3.15 for the downlink and equation 3.16 for the uplink:

$$R_j = \frac{R(N)}{n_T} \tag{3.15}$$

$$r_j = \frac{r(N)}{n_T} \tag{3.16}$$

This results in the traffic demand being evenly spread across the service area as shown in Figure 3.14.

The relationship between the coverage of the cell and the capacity of the cell appears to be linear when using shared-load evaluation compared to a uniformly

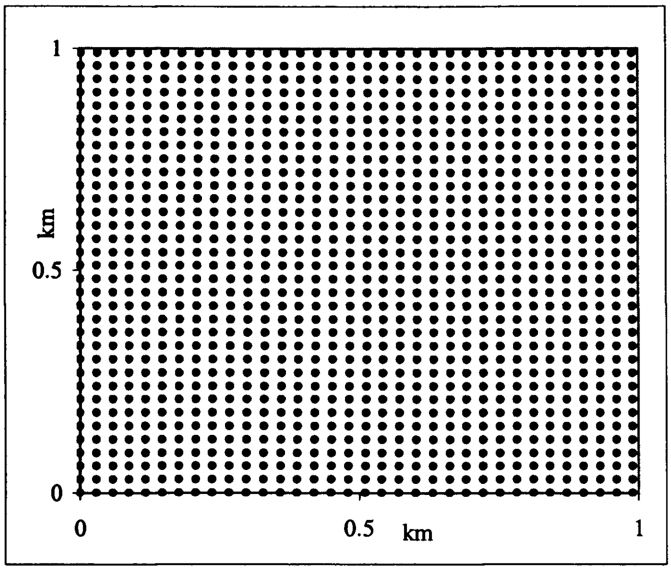


Figure 3.14: Regularly placed mobiles with shared traffic. Due to there being a mobile station located at each STP only a reduced region of the service area is shown in this figure, and the pattern repeats throughout the unseen region.

random or random-with cluster distributions. This can be illustrated by means of a simple example. Consider a 1km by 1km service area containing two sites, each having an associated omnidirectional antenna. Both antennae are configured identically, but the power of one antenna is repeatedly increased by 1 dBm, whilst the power of the second antenna remains constant. Between each power level, the network design is evaluated (Section 3.9).

Results indicate that for both uniformly random and random-with-cluster distributions the load of the cell can decrease or stay the same as the power of the antenna increases, as seen in figures 3.15, 3.16, 3.17 and 3.18. These results indicate a non-linear relationship between capacity and coverage. However, when the same test is performed for shared-load distribution (figures 3.19 and 3.20) it is seen that as the power setting of the antenna increases the number of mobile stations that can be supplied also increases and this results in the cell becoming more heavily loaded.

This characteristic of shared-load may be especially useful when being used as the underlying traffic distribution in optimisation. Each alteration to an antenna's configuration in the network results in a change to the shape of that cell.

Thus at each iteration in optimisation, an adjustment is made to the antenna's configuration, and the cost function value is highly likely to change. This could result in acceptance of good network adjustments that would not have altered the network, and therefore been accepted, if evaluating with uniformly random or random-with-cluster distributions.

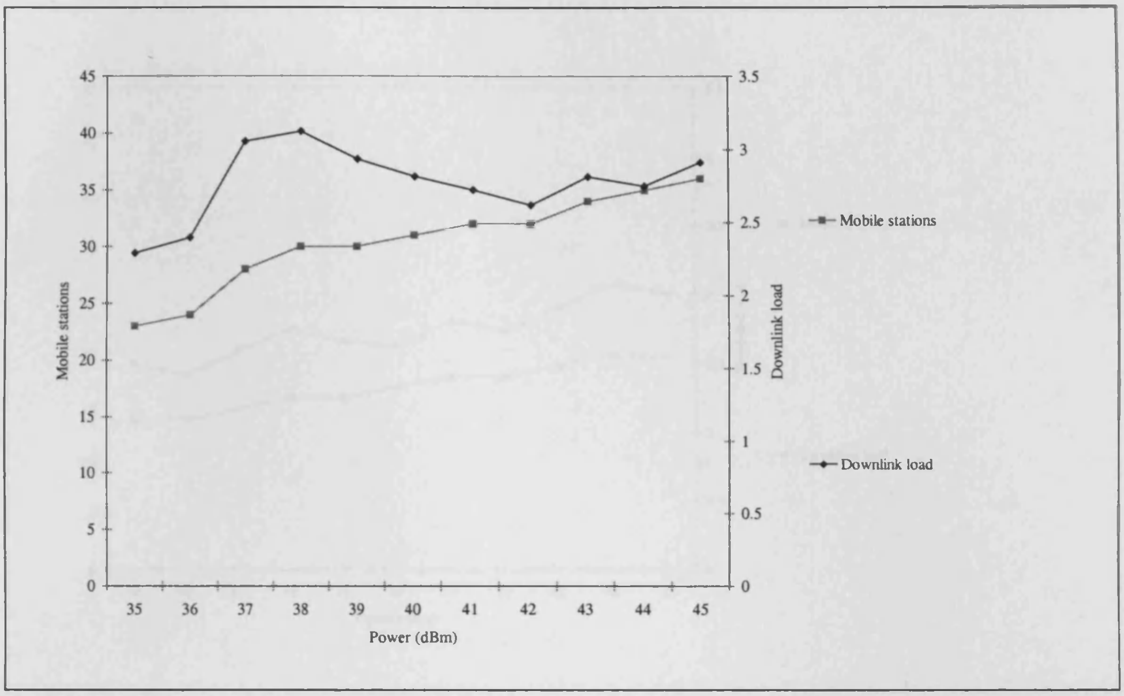


Figure 3.15: Evaluation with uniformly random distribution for downlink load

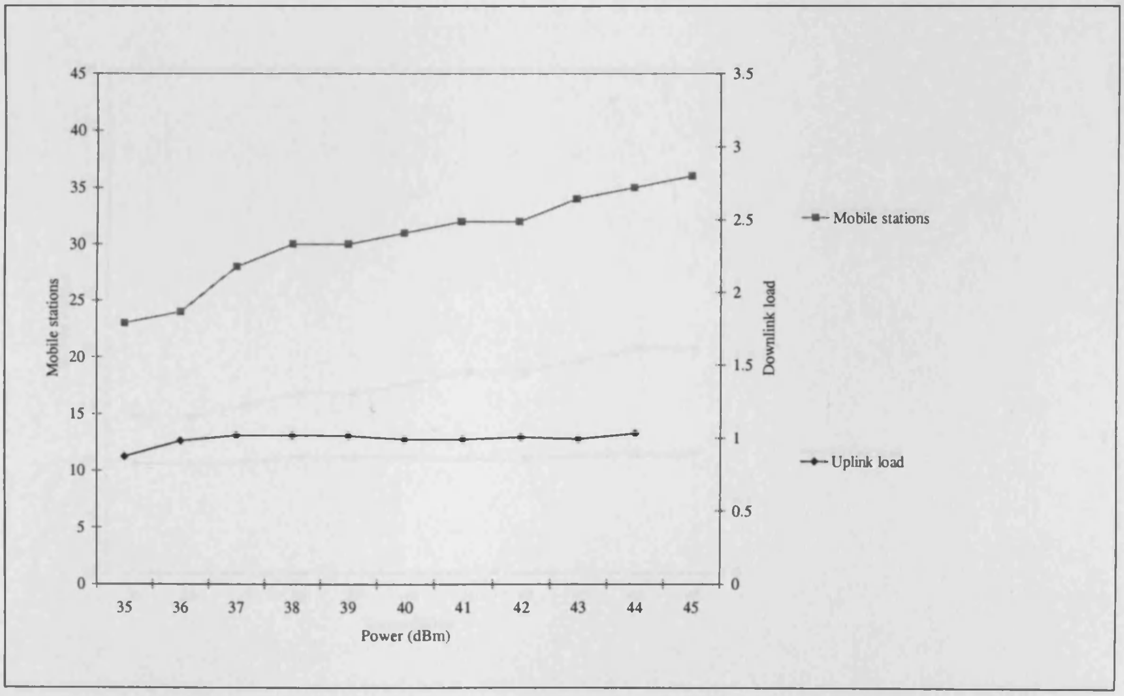


Figure 3.16: Evaluation with uniformly random distribution for uplink load

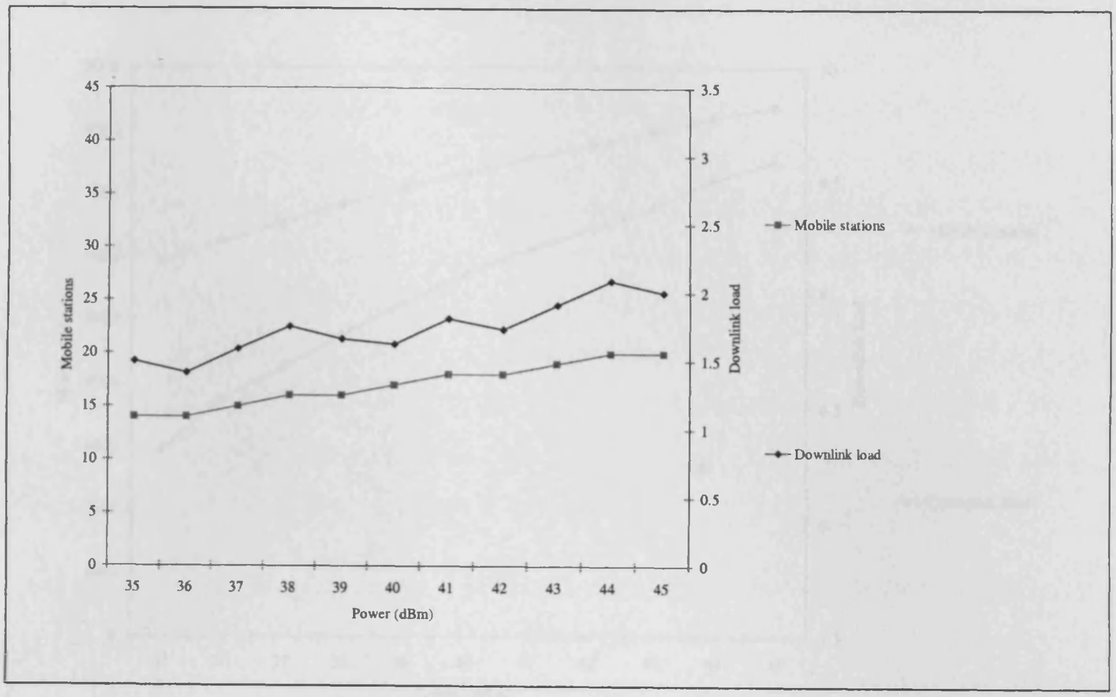


Figure 3.17: Evaluation using random-with-cluster distribution for downlink load

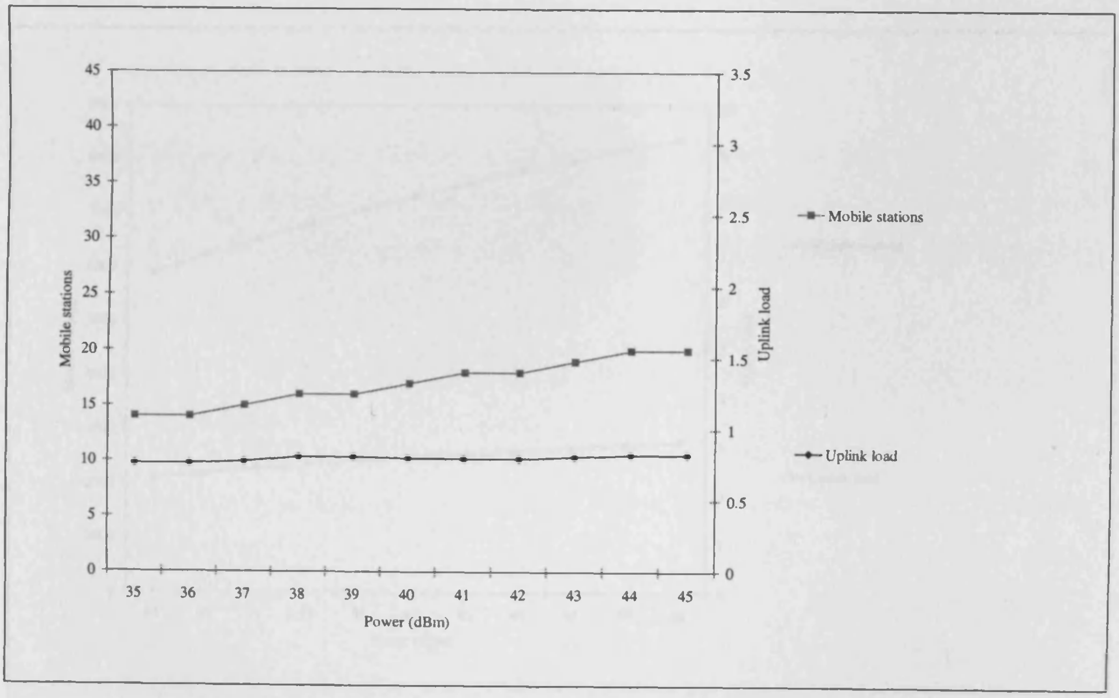


Figure 3.18: Evaluation using random-with-cluster distribution for uplink load

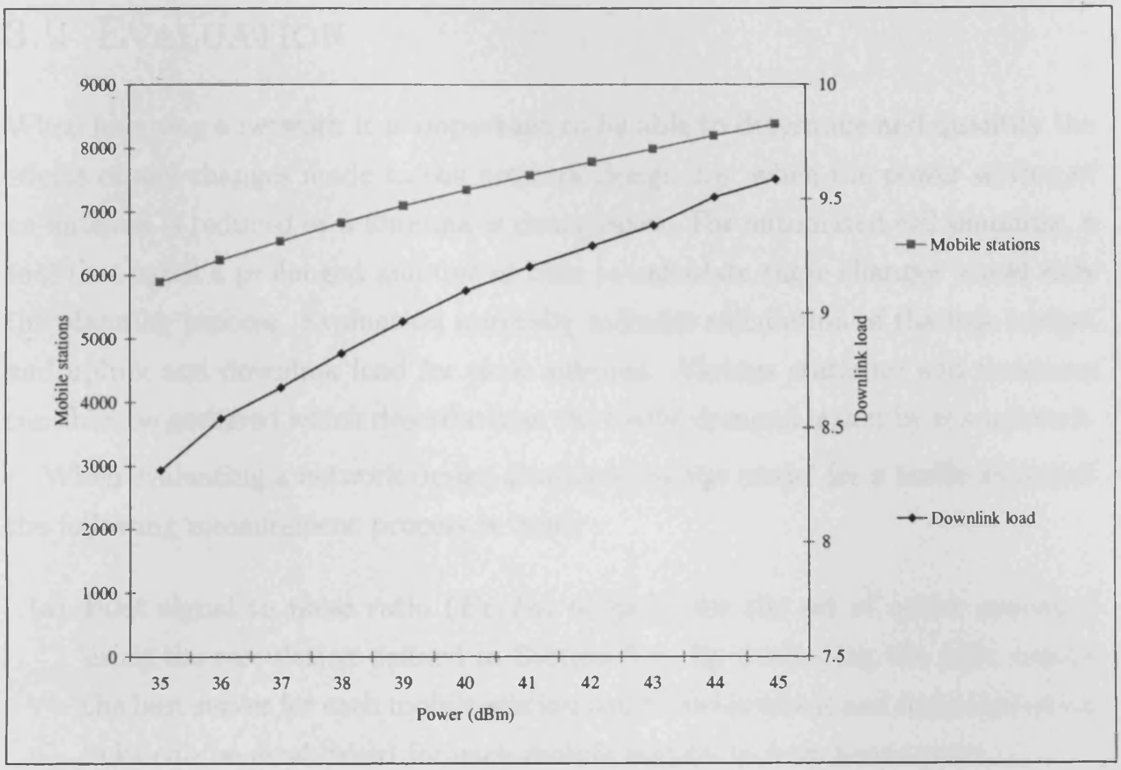


Figure 3.19: Evaluation with shared-load distribution for downlink load

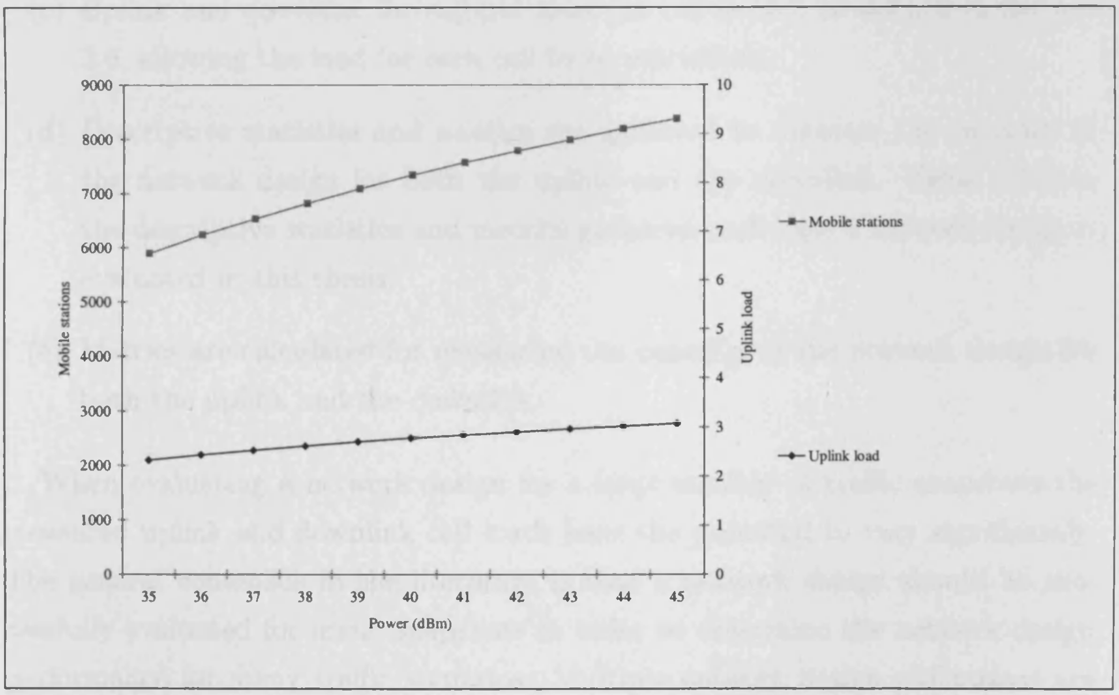


Figure 3.20: Evaluation with shared-load distribution for uplink load

3.9 EVALUATION

When planning a network it is important to be able to determine and quantify the effects of any changes made to the network design *e.g.* when the power setting of an antenna is reduced or a antenna is deactivated. For automated cell planning, a tool that takes a prolonged amount of time to calculate these changes would slow the planning process. Evaluation normally includes calculation of the link budget and uplink and downlink load for each antenna. Various statistics and measures can then be gathered which describe how the traffic demand is met by the network.

When evaluating a network design produced by the model for a traffic snapshot the following measurement process is used:

(a) Pilot signal to noise ratio (Ec/Io) is found for the set of active antennae using the calculation defined in Section 3.4. By evaluating the pilot signals the best server for each mobile station can be determined and communication links can be established for each mobile station to best server pair.

(b) Inter-cell and intra-cell interference is calculated at each cell.

(c) Uplink and downlink throughput load are calculated, as defined in Section 3.6, allowing the load for each cell to be calculated.

(d) Descriptive statistics and metrics are gathered to measure the capacity of the network design for both the uplink and the downlink. Table 3.5 lists the descriptive statistics and metrics gathered each time a network design is evaluated in this thesis.

(e) Metrics are calculated for measuring the capacity of the network design for both the uplink and the downlink.

When evaluating a network design for a large number of traffic snapshots the measured uplink and downlink cell loads have the potential to vary significantly. The general consensus in the literature is that a network design should be successfully evaluated for many snapshots in order to determine the network design performance for many traffic scenarios. Multiple network design evaluations are normally carried out by use of static system-level simulators. Static system-level simulators are discussed in detail by [23, 24, 78, 87] but are not applied in this

Statistic	Definition
Mean downlink cell load	$\frac{\sum_{k=1}^{n_{op}} \eta_{DL}(c_k)}{n_{op}}$
Mean uplink cell load	$\frac{\sum_{k=1}^{n_{op}} \eta_{UL}(c_k)}{n_{op}}$
Standard deviation of the downlink cell load	$\frac{\sum_{k=1}^{n_{op}} (\eta_{DL}(c_k) - \bar{x})}{n_{op}-1}$ ($\bar{x}$ = mean downlink cell load)
Standard deviation of the uplink cell load	$\frac{\sum_{k=1}^{n_{op}} (\eta_{UL}(c_k) - \bar{x})}{n_{op}-1}$ ($\bar{x}$ = mean uplink cell load)
Maximum downlink cell load	$\max_{k=0}^{n_{op}} \eta_{DL}(c_k)$
Maximum uplink cell load	$\max_{k=0}^{n_{op}} \eta_{UL}(c_k)$
Minimum downlink cell load	$\min_{k=0}^{n_{op}} \eta_{DL}(c_k)$
Minimum uplink cell load	$\min_{k=0}^{n_{op}} \eta_{UL}(c_k)$
Total network downlink load	$\sum_{k=1}^{n_{op}} \eta_{DL}(c_k)$
Total network uplink load	$\sum_{k=1}^{n_{c}op} \eta_{UL}(c_k)$
Downlink over-loaded cells	$\sum_{k=0}^{n_{op}} \left\{ \begin{array}{ll} 1 & \text{if } \eta_{DL}(c_k) > \text{(d + m)} \\ 0 & \text{otherwise} \end{array} \right\}$
Uplink over-loaded cells	$\sum_{k=0}^{n_{op}} \left\{ \begin{array}{ll} 1 & \text{if } \eta_{UL}(c_k) > \text{(d + m)} \\ 0 & \text{otherwise} \end{array} \right\}$
Downlink under-loaded cells	$\sum_{k=0}^{n_{op}} \left\{ \begin{array}{ll} 1 & \text{if } \eta_{DL}(c_k) < \text{(d - m)} \\ 0 & \text{otherwise} \end{array} \right\}$
Uplink under-loaded cells	$\sum_{k=0}^{n_{op}} \left\{ \begin{array}{ll} 1 & \text{if } \eta_{UL}(c_k) < \text{(d - m)} \\ 0 & \text{otherwise} \end{array} \right\}$
Cells with desired downlink load	$\sum_{k=0}^{n_{op}} \left\{ \begin{array}{ll} 1 & \text{if (d - m)} < \eta_{DL}(c_k) < \text{(d + m)} \\ 0 & \text{otherwise} \end{array} \right\}$
Cells with desired uplink load	$\sum_{k=0}^{n_{op}} \left\{ \begin{array}{ll} 1 & \text{if (d - m)} < \eta_{UL}(c_k) < \text{(d + m)} \\ 0 & \text{otherwise} \end{array} \right\}$
Total downlink network over-loading	$\sum_{k=1}^{n_{op}} \{\eta_{DL}(c_k) - \text{(d + m)}\}$
Total uplink network over-loading	$\sum_{k=1}^{n_{op}} \{\eta_{UL}(c_k) - \text{(d + m)}\}$

Table 3.5: Measures and metrics that are gathered for each network design after evaluation.

thesis. Instead, the network dimensioning process presented in chapters 4 and 5 is used to validate network performance and this process is discussed in detail in Chapter 7.

3.10 NETWORK DESIGN OBJECTIVES

Access limitations to operator defined targets make it difficult to quantitatively evaluate a network design. These limitations extend to the open literature: even though many authors assert its importance for cell planning evaluation, few provide details on the subject. This makes evaluating a single network design difficult. Most design objectives normally involve some combination of the following:

- maximising capacity;
- maximising coverage;
- maximising quality of service provided to subscribers;
- minimising infrastructure requirements;
- maximising revenue;
- minimising expenses.

This thesis considers network evaluation as a comparison operation by trying to make design adjustments to attain an improved network design. The task of quantifying a network's performance is made more difficult when trying to optimise multiple objectives. The objectives to be met in this work are

- improving mean uplink and downlink cell load with the aim of meeting a specified cell load target;
- minimising the number of deployed sites and antennae
- reducing the amount of network overloading in the uplink and downlink;
- maximising the number of supplied mobile stations;
- maximising the number of covered STP.

The balance of priority of these objectives will change at different stages of the automated cell planning process. For example in network dimensioning the aim is to find an initial network design with an average cell load that is as close as possible to the desired cell load, whilst the optimisation stage will consider all the objectives above with varying priority. Multiple objectives are addressed in Chapter 6 along with the optimisation framework.

Chapter 4

Network Dimensioning

In a WCDMA network it is desirable to maximise the capacity, coverage and quality of service achieved. Network dimensioning techniques can be used to provide the first estimate of the network's capabilities in terms of these three essential attributes [41, 57]. The main objective of dimensioning is to simplify the complex task of network planning by making the necessary estimations and assumptions concerning the hardware or resources required to provide a satisfactory service. Laiho, Wacker, and Novosad [50] promote a practical approach stating that the target of network dimensioning should be to provide an estimate of the number of sites for selection and to specify initial site configuration.

It was seen in Chapter 2 that capacity dimensioning has been less well studied in comparison to coverage dimensioning and this provides the motivation for incorporating capacity network dimensioning into the solution framework. Previous work on network dimensioning has failed to explicitly specify the number of sites required to meet capacity specifications and the need for dimensioning techniques capable of considering both the uplink and downlink is highlighted. When the target of network dimensioning is to estimate the number of sites for selection it becomes homologous with providing lower bounds. The only published bounds for third generation systems were given by Allen *et al.* [7]. This chapter considers the possible application of load factor equations used in the lower bounding techniques presented in [7] to help determine an initial number of sites for selection as part of an overall cell planning framework. Specifically, a number of new contributions to the field of automated cell planning are made including:

- the development of a new network dimensioning technique (which is completed in Chapter 5);
- the use of equations previously developed as part of a lower bounding technique, as a first step in network dimensioning;
- an analysis of the effects of the network dimensioning process with regards to the UMTS network model presented in this thesis.

4.1 ESTIMATING SITE REQUIREMENTS

In 3GSTART [7], load factor equations are used to predict the number of sites required to meet capacity targets, whilst link budget calculations are used to predict the number of sites required to meet coverage targets. This investigation concentrates on the effect of capacity dimensioning on network planning. Firstly, the load factor equations presented in Chapter 3 are manipulated as suggested in 3GSTART and applied in a new way to assist with estimating the number of sites required.

This first stage in network dimensioning can be sub-divided into a number of steps concerning uplink and downlink load factor equations. Load factor equations are concerned with estimating the amount of traffic that can be supported by each site in the network design. For purposes of network dimensioning, if the desired load factor is known, equations can be manipulated to determine the number of users that can be supported by a single site. Hence the total number of antennae required to supply the service area can be determined. The four steps involved in the process for estimating the required number of sites are explained below any assumptions follow from 3GSTART equations:

STEP 1 : Obtain load target for a cell and other parameter inputs.

STEP 2 : Calculate downlink load.

In Chapter 3 the downlink throughput load, $\eta_{DL}(c_k)$, of cell c_k was defined. In 3GSTART this equation is adapted to consider an average cell*, c, by assuming v_j, $(E_b/N_o)_j$, R_j, α_j and I_j^{DL} are the same for

*From this assumption it is likely that edge effects will be experienced in cells on the edge of the service area, but for representative network data sets this effect is likely to be minimal.

all users of the same service. General values are therefore used for v, E_b/N_0, R, α and I^{DL} giving

$$\eta_{DL}(c) = n_u(c)\ v\frac{(E_b/N_o)}{W/R}[(1-\alpha)+I^{DL}] \tag{4.1}$$

Equation 4.1 is further adapted to consider the number of services, n_f, that are included in the service mix

$$\eta_{DL}(c) = \sum_{f=1}^{n_f} \lambda_f\ n_u(c)\ \sigma_f^{DL} \tag{4.2}$$

where λ_f denotes the proportion of users utilising service f and σ_f^{DL} is defined as

$$\sigma_f^{DL} = \left(v\ \frac{(E_b/N_o)}{(W/R)}[(1-\alpha)+I^{DL}]\right)$$

The number of users that can be supported by c in the downlink with a target load η_{DL} is given as

$$n_u^{DL}(c) = \frac{\eta_{DL}}{\sum\limits_{f=1}^{n_f} \lambda_f \sigma_f^{DL}} \tag{4.3}$$

STEP 3 : Calculate uplink load.

The uplink load factor equation for a given service mix with n_f services is defined

$$\eta_{UL}(c) = \sum_{f=1}^{n_f} \lambda_s\ n_u(c)\ \sigma_f^{UL} \tag{4.4}$$

where σ_f^{UL} is now defined as

$$\sigma_f^{UL} = (1+i)\left(1+\frac{W}{(E_b/N_o)\ R\ v}\right)^{-1}$$

The number of users that can be supported by c in the uplink with a target load η_{UL} is given as

$$n_u^{UL}(c) = \frac{\eta_{UL}}{\sum_{f=1}^{n_f} \lambda_f \sigma_f^{DL}} \tag{4.5}$$

STEP 4 : Calculating site requirements.

Given the user density, u_d, and the number of simultaneously active users, κ, the area $a(c)$, of a cell c, can be defined

$$a(c) = \frac{n_u^{max}(c)}{u_d \times \kappa} \tag{4.6}$$

where $n_u^{max}(c) = \max n_u^{DL}(c), n_u^{UL}(c)$. This allows the number of sites per square kilometre to be determined via

$$\text{sites per sq. km} = \frac{1}{a(c)} \tag{4.7}$$

If a site is sectorized, for example has three antennae directional antenna ($n_B(S) = 3$), 3GSTART assumes that it will have three times more capacity capability than if it had a single omnidirectional antenna. In this case the number of sites required for selection is reduced, becoming

$$\text{omnidirectional sites per sq.km} = \frac{\text{sites per sq.km}}{3} \tag{4.8}$$

The total number of sites required to provide service to the working area is defined

$$\text{total sites} = \lceil \text{sites per sq. km} \times M \rceil \text{ in sq. km} \tag{4.9}$$

If the estimated number of sites originates from the downlink load equation then it is said to be *downlink-estimated.* Likewise if the estimated number of sites originates from the uplink load equation then it is said to be *uplink-estimated.*

4.2 ANALYSIS

The downlink-estimate and uplink-estimate can be tested by checking that the load factor equations produce the correct output for a given set of parameter values. In order to test the network dimensioning process a number of different network designs can be generated from the KORNET1 and KORNET2 data sets using the model in Chapter 3 and the estimated number of sites deployed. The downlink-estimate and the uplink-estimate can then be compared to the average downlink cell load and the average uplink cell load obtained from each network design when evaluated using methods presented in Chapter 3. This allows the differences between the analytical approach to network dimensioning and the actual model to be quantified, as suggested by Molkdar *et al.* in [61].

A downlink-estimated number of sites are selected from the candidate set of sites at random. The random number generation used throughout is performed using a pseudo-random number generator, which allows uniformly random numbers to be generated from two recorded seeds. For experimentation purposes all the selected sites are configured with either one omnidirectional antenna or three directional antennas, resulting in the network design having either all omnidirectional antennas or all directional antennas. Each antenna A_k belonging to a selected site has power setting $P_k^A = 40\text{dBm}$ and tilt setting $A_k^\beta = 0°$. If the site is sectorized, the first directional antenna has an azimuth setting of $A_k^\delta = 0°$, the second directional antenna has an azimuth of $A_k^\delta = 120°$ and the third directional antenna has an azimuth of $A_k^\delta = 240°$. A network design is formed from all the operational antennae and is evaluated based on procedures explained in Chapter 3 for one snapshot evaluation.

By calculating the mean cell load of the network design, comparison can be made with the desired average cell load target specified as the input to the estimation algorithm, $\eta_{DL}(c)$, as shown in Figure 4.1. The series named *Downlink-estimated* in Figure 4.1 is obtained by finding the mean downlink cell load of the modelled network design. This is achieved by finding the mean of the column entitled '$\eta_{DL}(c_k)$' in Table 4.1.

The data points that comprise the series in Figure 4.1 provide examples of the average cell loads obtained when different numbers of sites are operational.

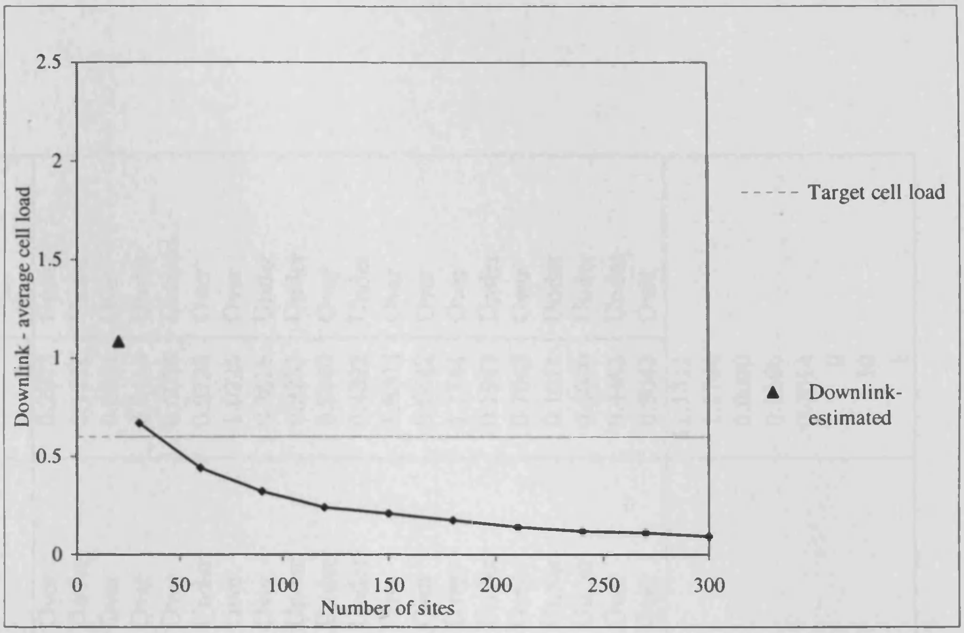


Figure 4.1: Graph showing the downlink-estimate for a rural scenario

Each point on the graph is produced from a line in Table 4.2 and each line in Table 4.2 is produced from a table similar to that shown in Table 4.1. The list below explains some of the column titles used in Table 4.2:

- 'Des' represents the number of cells with a desired load;
- 'Over' represents the the number of over-loaded cells;
- 'Under' represents the number of under-loaded cells;
- 'STDEV' represents the standard deviation;
- 'Total over $d+m$' represents the total amount of over-loading in the network.

These abbreviations are used in the remainder of the thesis.

The same test is performed using the uplink load equation to determine the number of operational sites required. Figure 4.2 shows the average uplink cell load against the number of operational sites. Figures 4.3 and 4.4 illustrate the results obtained for a suburban environment and figures 4.5 and 4.6 illustrate results obtained for an urban environment. Both uplink-estimated and downlink-estimated

	P^{A_k}	A_k^{δ}	A_k^{β}	A_k	STP	$n_u(c_k)$	$\eta_{DL}(c_k)$	$\eta_{DL}(c_k)$ state	$\eta_{UL}(c_k)$	$\eta_{UL}(c_k)$ state
Antenna1052_0	40	0	0	Omni	1221	6	0.7212	Over	0.2973	Under
Antenna1247_0	40	0	0	Omni	520	3	0.2715	Under	0.1227	Under
Antenna1182_0	40	0	0	Omni	4724	23	1.1528	Over	0.6961	Over
Antenna1019_0	40	0	0	Omni	1420	9	0.7796	Over	0.2413	Under
Antenna1211_0	40	0	0	Omni	3395	19	1.7912	Over	0.6064	Desired
Antenna1118_0	40	0	0	Omni	1600	4	0.5049	Under	0.9725	Over
Antenna1111_0	40	0	0	Omni	4605	18	1.5803	Over	1.0225	Over
Antenna1078_0	40	0	0	Omni	2116	11	0.7392	Over	0.3618	Under
Antenna1188_0	40	0	0	Omni	1080	3	0.2330	Under	0.2237	Under
Antenna1262_0	40	0	0	Omni	1311	4	0.5341	Under	0.8960	Over
Antenna1164_0	40	0	0	Omni	2550	8	0.5254	Under	0.4392	Under
Antenna1139_0	40	0	0	Omni	8311	39	1.7755	Over	1.0803	Over
Antenna1220_0	40	0	0	Omni	2083	12	1.3388	Over	0.6842	Over
Antenna1293_0	40	0	0	Omni	4317	25	4.7686	Over	1.1744	Over
Antenna1166_0	40	0	0	Omni	1121	9	0.4916	Under	0.1947	Under
Antenna1253_0	40	0	0	Omni	3958	13	1.3920	Over	0.7643	Over
Antenna1287_0	40	0	0	Omni	1117	3	0.1425	Under	0.1011	Under
Antenna1157_0	40	0	0	Omni	866	0	0.0000	Under	0.0000	Under
Antenna1073_0	40	0	0	Omni	1973	9	0.8285	Over	0.4483	Under
Antenna1090_0	40	0	0	Omni	6930	27	2.1113	Over	0.8043	Over
						Sum	21.6819		11.1311	
						Max	4.7686		1.1744	
						Min	0.0000		0.0000	
						Mean	1.0841		0.5566	
						STDEV	1.0557		0.3614	
						#Over	12		9	
						#Under	8		10	
						#Desired	0		1	

Table 4.1: Uplink and downlink cell throughput load result produced from one network design evaluation.

% n_{op}^S	n_{op}^S	n_{op}	Max $\eta_{DL}(c_k)$	Min $\eta_{DL}(c_k)$	Mean $\eta_{DL}(c_k)$	STDEV $\eta_{DL}(c_k)$	$\sum_{k=0}^{n_{op}} \eta_{DL}(c_k)$	Des c_k	Over c_k	Under c_k	Total over $d+m$
10	30	30	1.7465	0	0.6684	0.4123	20.0520	3	5	22	6.9436
20	60	60	1.6254	0	0.4423	0.3272	26.5380	3	5	52	5.5981
30	90	90	1.3475	0	0.3236	0.2378	29.1256	1	3	86	4.6313
40	120	120	1.9143	0	0.2401	0.1898	28.8110	2	2	116	3.7093
50	150	150	1.5740	0	0.2101	0.1644	31.5124	2	1	147	3.1369
60	180	180	1.7236	0	0.1739	0.1394	31.2963	0	1	179	3.1363
70	210	210	1.5049	0	0.1408	0.1166	29.5772	0	1	209	1.7526
80	240	240	1.2087	0	0.1201	0.1088	28.8332	0	1	239	1.0609
90	270	270	0.9267	0	0.1102	0.0891	29.7540	0	0	270	0.9812
100	300	300	0.8341	0	0.0925	0.0769	27.7608	0	0	300	0.2422
Downlink-estimated	20	20	4.7686	0	1.0841	0.6508	21.6819	1	9	10	11.0589

Table 4.2: Downlink load comparison results for KORNET1 considering a rural environment for a mixed service. Each line in the table represents a summary of results gathered from tables similar to table 4.1 for a single network evaluation.

tests are carried out for KORNET1 and KORNET2 data sets also considering rural, suburban and urban user density scenarios for a mixed service for both omnidirectional initial configuration and directional initial configuration.

Figure 4.1 shows that 20 sites, each configured with one omnidirectional antenna, are required for activation as a result of the downlink-estimate. The average cell load of the network design is approximately 1.0 (greater than the target cell load plus allowed margin). By looking at the graph it can be seen that approximately 40 sites would need to be activated for downlink-estimated average cell load to meet the desired cell load.

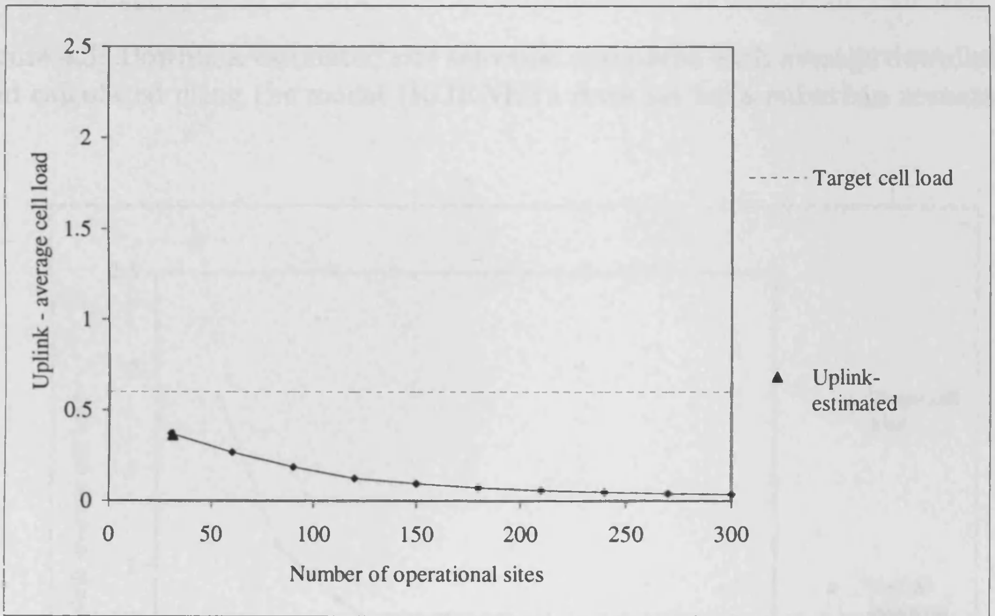


Figure 4.2: Uplink-estimated site selection compared with average uplink cell load calculated using the model (KORNET1 data set for a rural scenario)

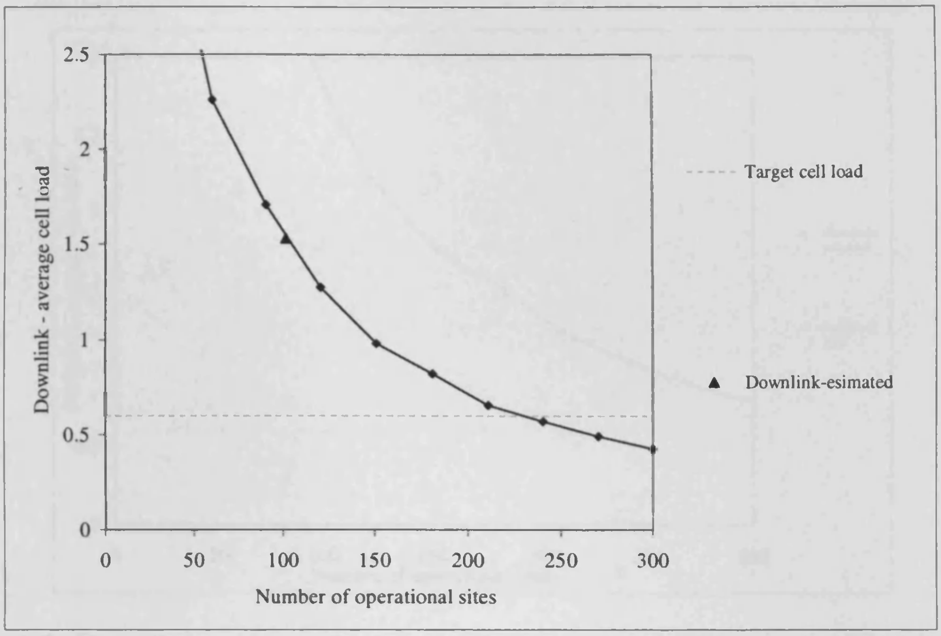


Figure 4.3: Downlink-estimated site selection compared with average downlink cell load calculated using the model (KORNET1 data set for a suburban scenario)

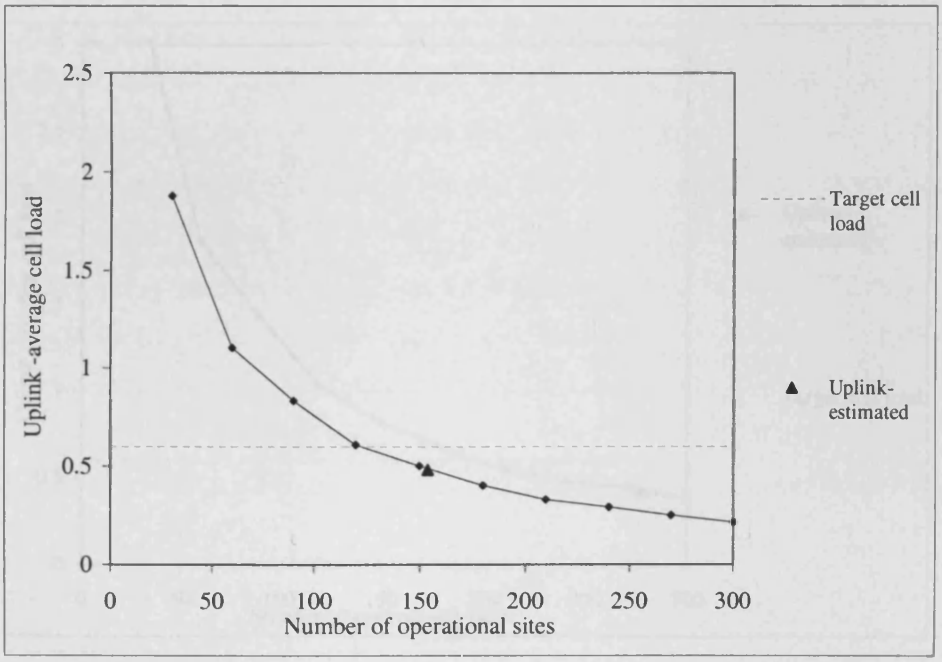


Figure 4.4: Uplink-estimated site selection compared with average uplink cell load calculated using the model (KORNET1 data set for a suburban scenario)

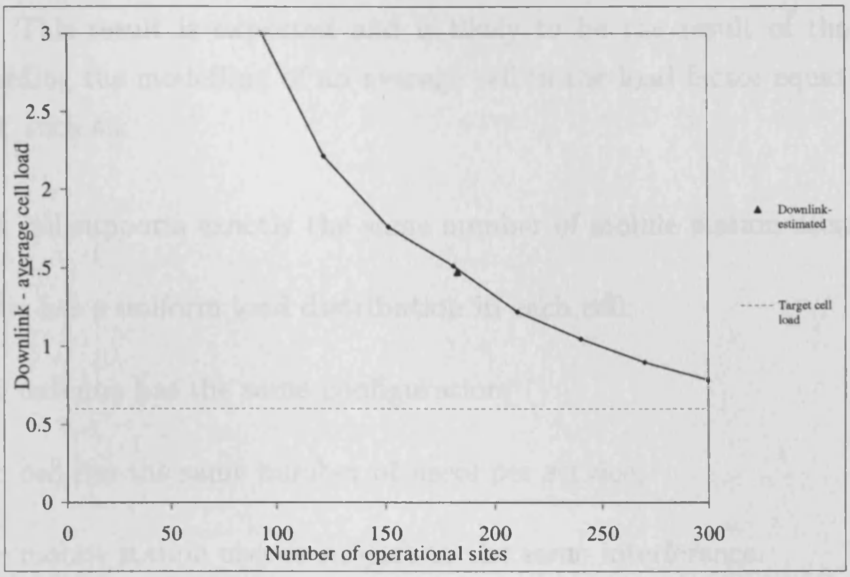


Figure 4.5: Downlink-estimated site selection compared with average downlink cell load calculated using the model (KORNET1 data set for an urban scenario)

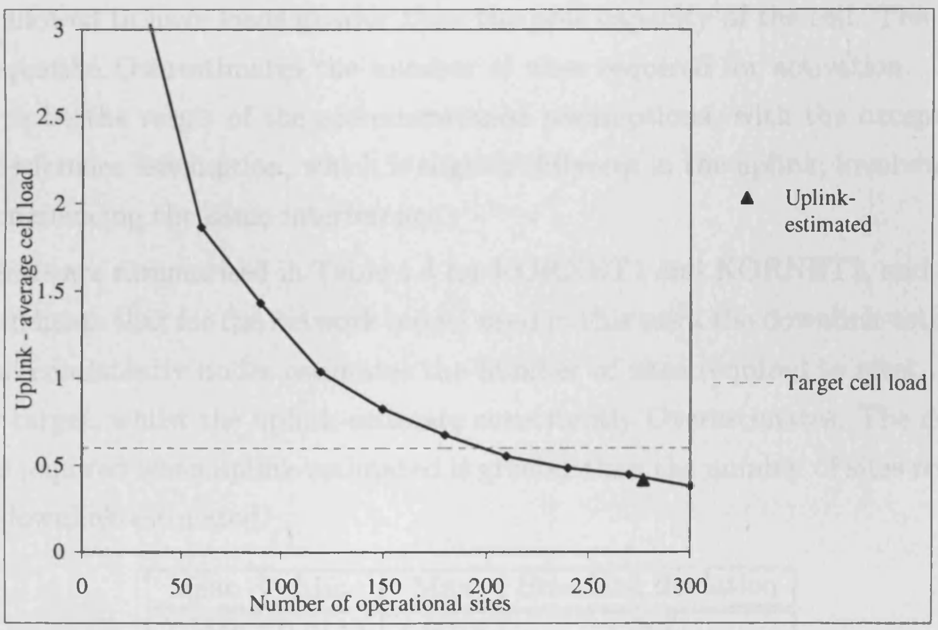


Figure 4.6: Uplink-estimated site selection compared with average uplink cell load calculated using the model (KORNET1 data set for an urban user scenario)

The downlink-estimated method slightly under estimates the number of sites required. This result is expected and is likely to be the result of the assumptions regarding the modelling of an average cell in the load factor equations from 3GSTART such as:

(a) each cell supports exactly the same number of mobile station users;

(b) traffic has a uniform load distribution in each cell;

(c) each antenna has the same configuration;

(d) each cell has the same number of users per service;

(e) each mobile station user is subject to the same interference.

The main problem is due to the assumptions concerning interference. The average interference ratio experienced in the downlink at each mobile station is specified to be 0.55, whereas the interference experienced at the mobile station in the actual model is much higher (see statistics in Table 4.3). This is due to cells being allowed to have loads greater than the pole capacity of the cell. The uplink load equation Overestimates the number of sites required for activation. This is likely to be the result of the aforementioned assumptions, with the exception of the interference assumption, which is slightly different in the uplink, involving each site experiencing the same interference.

Results are summarised in Table 4.4 for KORNET1 and KORNET2, and collectively indicate that for the network model used in this work the downlink-estimated method consistently under estimates the number of sites required to meet the capacity target, whilst the uplink-estimate consistently Overestimates. The number of sites required when uplink-estimated is greater than the number of sites required when downlink-estimated.

Mean	Min	Max	Standard deviation
1.2556	0.0145	4.6618	1.0881

Table 4.3: Example of the downlink interference ratio experienced in the network model (rural scenario)

4.2.1 TUNING

There is scope for improvement and possible tuning of the estimate should be considered as a starting point for optimisation. Tuning could take one of the following forms:

Option A: Calculate both the uplink-estimate and downlink-estimate each time network dimensioning is performed to allow the selection of the highest estimate.

Option B: Perform a number of preliminary tests to determine whether the downlink-estimate or the uplink-estimate is generally better with the network model in use. This would allow the same decision to be made whenever carrying out network dimensioning using the same network model.

Option C: Introduce correction factors to apply to each estimate to improve the estimate by getting closer to the desired cell load.

Option A in the above list involves using the method suggested in 3GSTART, which selects the highest from the uplink-estimate and downlink-estimate to determine the number of sites selected. If this method is used with this model the uplink-estimate would be used. As the uplink-estimate consistently Overestimates the number of sites required for selection it would increase the number of operational sites *i.e.* unused capacity in the uplink.

Option B provides an alternative by selecting the estimate that produces the best nominal network design with respect to the operator's requirements. This would involve tuning the estimation algorithm to the model and may therefore result in different decisions being made for different models. The flowchart in Figure 4.7 can be applied to a number of preliminary tests to determine, in general, whether the uplink-estimate or the downlink-estimate provides the best value. This algorithm attempts to pick the value that is the closest to the desired cell load for both the uplink and the downlink. Tuning tests would need to be carried out each time a new model is used with the network dimensioning process and this could be easily automated. In this case applying Figure 4.7 to the tests carried out for KORNET1 and KORNET2 suggests the downlink-estimate should be used to determine the number of sites required for selection this decision is advantageous for the following reasons:

(a) as the uplink-estimated method consistently Overestimates the number of sites required for selection, site selection using the downlink-estimate that consistently requires less sites will bring the average uplink load closer to the desired uplink cell load;

(b) the downlink-estimated method consistently activates less sites than the uplink-estimated, which helps to minimise the number of operational sites in the network;

(c) even though the number of sites when determined by the downlink-estimated method is Underestimated, this gap may be reduced via use of network optimisation and tuning techniques.

The decision process for selecting the best estimate is likely to change subject to the operator's/vendor's network design objectives. For example the case where the highest estimate is selected would be more appropriate if the operator wants to produce a nominal cell plan for budgetary purposes with no optimisation, as it would select the uplink-estimate to determine the number of operational sites for both KORNET1 and KORNET2. The flowchart in Figure 4.7 favours using the downlink-estimate and it is recommended that this method be used when operators want to produce a cell plan that minimises the number of sites and reduces uplink wasted capacity, before undertaking network optimisation to reduce the downlink load.

Options A and B present a trade-off between accuracy and time. By performing preliminary tests a decision can be made and used consistently *e.g.* always use the downlink-estimate, saving time as both estimates do not have to be calculated each time estimating the number of sites is undertaken. Accuracy is sacrificed as sometimes it might be better to activate the uplink rather than the downlink, resulting in the best estimate not being chosen.

Option C involves trying to improve the downlink-estimate and uplink-estimate by increasing or reducing the number of sites by a proportion of the initial estimate. For example consider KORNET1 and KORNET2 results for downlink-estimated. By multiplying each the number of operational sites (determined by the estimate)

Data	A_k	u_d type	Target $\eta_{DL}(c)$	Downlink-estimate $\eta_{DL}(c)$	Downlink-estimate n_{op}	Target downlink n_{op}	Target $\eta_{UL}(c)$	Uplink-estimate $\eta_{UL(c)}$	Uplink-estimate n_{op}	Target uplink n_{op}
K1	Omni	Rur	0.6	0.9797	20	40	0.6	0.3850	31	<31
		Sub	0.6	1.0037	101	230	0.6	0.3606	154	120
		Urb	0.6	0.9458	182	>300	0.6	0.2914	277	190
K1	Dir	Rur	0.6	0.9185	21	<90	0.6	0.3284	30	<90
		Sub	0.6	1.1040	102	240	0.6	0.4053	153	90
		Urb	0.6	1.2167	183	440	0.6	0.4819	276	180
K2	Omni	Rur	0.6	0.8871	41	<90	0.6	0.3551	63	<90
		Sub	0.6	1.3947	206	300	0.6	0.4743	314	140
		Urb	0.6	1.4078	372	560	0.6	0.4367	565	420
K2	Dir	Rur	0.6	0.7613	42	<210	0.6	0.3538	63	<210
		Sub	0.6	1.0478	207	420	0.6	0.3903	315	420
		Urb	0.6	1.1920	375	840	0.6	0.4401	564	840

Table 4.4: This table shows site estimation results for KORNET1 and KORNET2 data sets. For each data set rural, suburban and urban user density environments have been considered for a mixed service.

roughly by 2, the number of sites is brought into the approximate range required to meet the desired cell load of 0.6. Figure 4.8 demonstrates the result of increasing the estimate obtained for a rural environment by a factor of 2. It is seen that the new estimate achieves an average cell load of approximately 0.58. This extra tuning may be useful if further optimisation is not going to be performed and a nominal cell plan needs to be produced for budgetary purposes. Alternatively, if further optimisation is going to be performed it might be necessary to firstly improve the estimate by multiplying by a factor to provide a better starting point for the optimisation. The appropriate multiplication factor is likely to vary between the uplink and downlink and from one scenario to another. Preliminary tests would have to be carried out to determine a suitable factor. Future work could involve automating the tuning options.

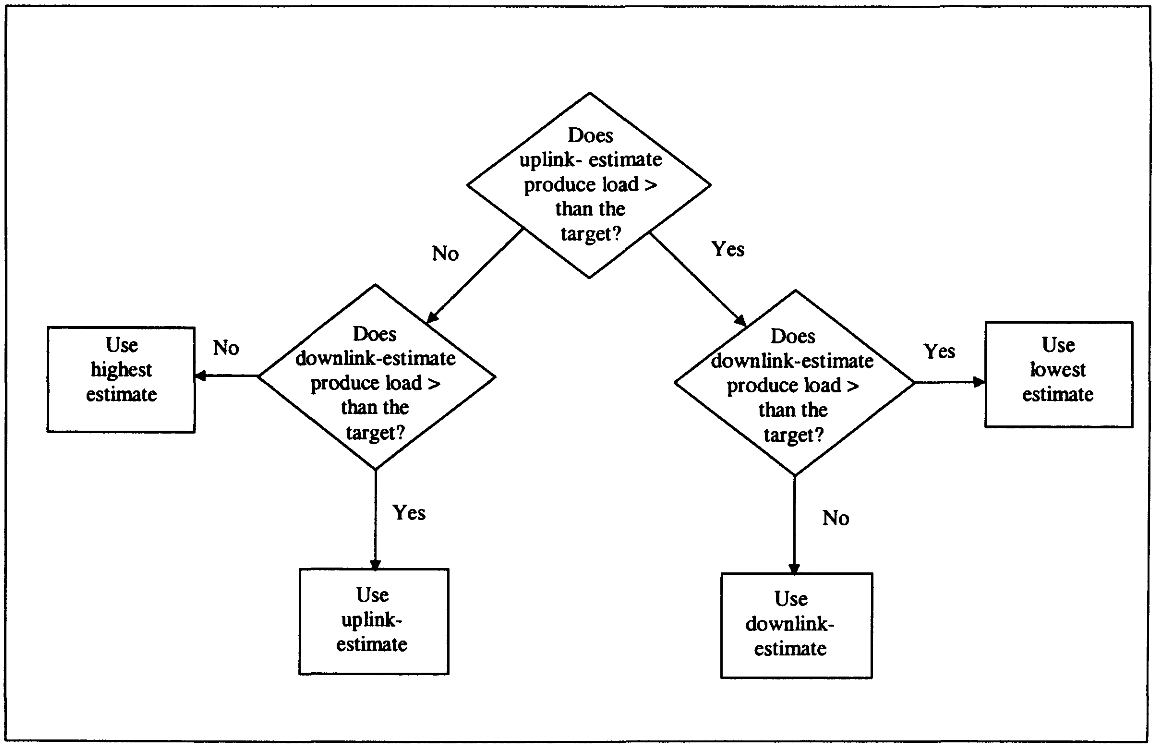


Figure 4.7: Decision process for capacity limited situation for tuning the site estimate

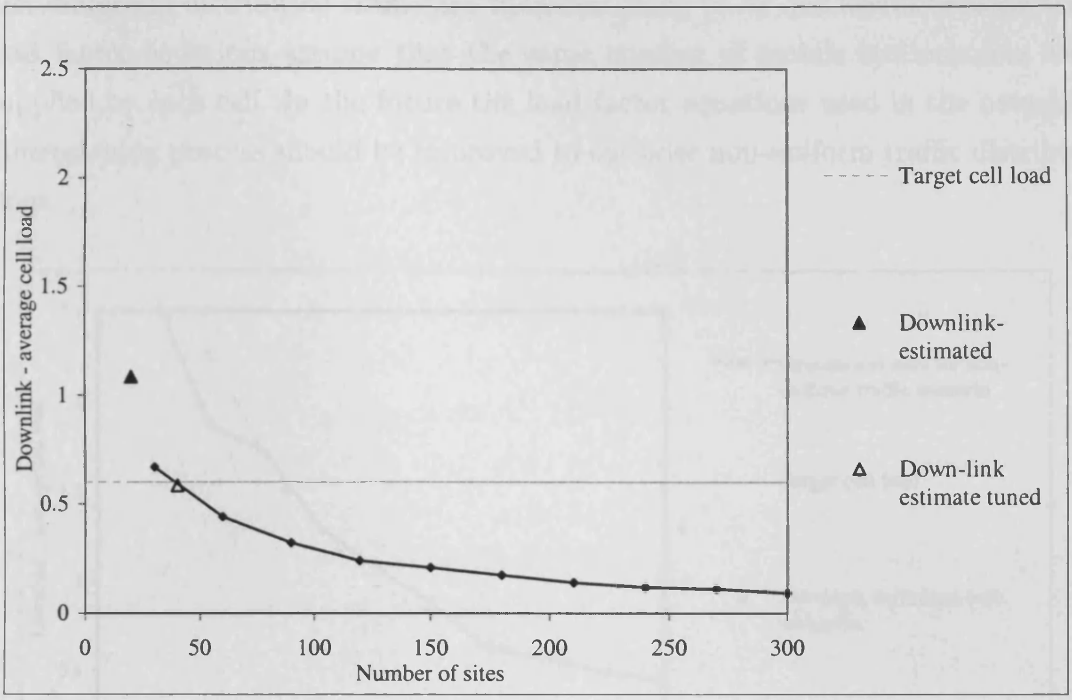


Figure 4.8: Using the downlink-estimated load equation to determine the number of operational sites and tuning by multiplying the estimate by a factor of 2. This example uses the KORNET1 data set and considers a rural environment for a mixed service scenario

4.2.2 NON-UNIFORMLY DISTRIBUTED TRAFFIC

Estimating the network's site requirements is considered for a non-uniform traffic scenario which uses the 'random-with-cluster' distribution. Results indicate that the method for estimating site requirements is not as compatible for different traffic distributions and also requires tuning to improve the initial network design. Figure 4.9 provides an example where each site is has a single omnidirectional antenna and the network operates in a suburban traffic scenario. The series in figure 4.9 appears to not be as smooth as the the series produced for the same network when rural traffic was uniformly randomly distributed (Figure 4.1). When considering a random distribution of mobile stations, each cell in the network design is potentially able to cover a similar amount of traffic because each mobile station is equally likely to be positioned at a STP. However, when considering a cluster distribution each cell is less likely to cover a similar amount of traffic making for a less smooth series. Estimations produced when the planning scenario involves non-uniformly distributed traffic are therefore likely to be less useful because the load factor equations assume that the same number of mobile station users are supplied by each cell. In the future the load factor equations used in the network dimensioning process should be improved to consider non-uniform traffic distributions.

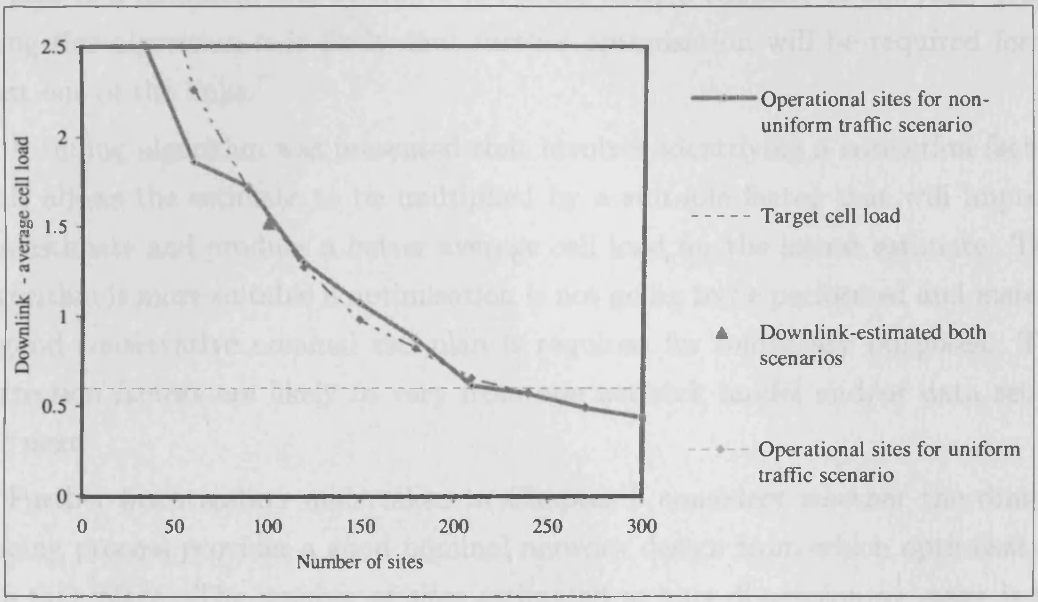


Figure 4.9: Non-uniform traffic (suburban)

4.3 SUMMARY

Results indicate that the network dimensioning process is able to produce a reasonable estimate of the number of sites required for selection. The equations used in 3GSTART [7] could be improved to take into account scenarios with non-uniform traffic, mixed omnidirectional and directional antenna cell plans and better interference modelling in both the uplink and the downlink. Alternatively, the estimates produced can be improved by incorporating into the dimensioning process certain algorithms which allow either the best estimate to be selected or one or both of the estimates to be improved upon. The network dimensioning process can then be used to assist in producing an initial cell plan for budgetary purposes or as a first stage in the automated cell planning process. It is recommended that the process be tuned to the network model and a number of algorithms have been presented and discussed for doing this effectively in light of the planning objectives.

An algorithm is presented which attempts to select the best estimate or estimate that is closest to the average cell load for one of the traffic directions. This is recommended when operators need to produce a cell plan that keeps the number of sites to a minimum and attempts to reduce unused capacity in one link. When using this algorithm it is likely that further optimisation will be required for at least one of the links.

A tuning algorithm was presented that involves identifying a correction factor. This allows the estimate to be multiplied by a suitable factor that will improve the estimate and produce a better average cell load for the lowest estimate. This algorithm is more suitable if optimisation is not going to be performed and instead a good conservative nominal cell plan is required for budgetary purposes. The correction factors are likely to vary from one network model and/or data set to the next.

Further investigation undertaken in Chapter 6 considers whether the dimensioning process provides a good nominal network design from which optimisation can take place. The number of sites estimated at this dimensioning stage is intended to be an approximate guide to the number of candidate sites that will be considered in the next stage of the planning process.

Chapter 5

Site Selection

The process for identifying useful sites for deployment in a network is time consuming and can sometimes result in a delay in the network's launch. Operators suffer restrictions in acquiring property at key locations that are normally affected by high prices and local demand. The selected sites form the basis of a cellular network that will need to satisfy certain requirements at roll-out and for the duration of the network's deployment.

When the number of sites required for deployment in the network is fixed there are many different possible site selections and configurations that can be made. As discussed in Chapter 3 the process for selecting site locations is not explicitly stated or explained by authors and the application sophisticated techniques to assist in making this decision is not evident. It is possible that processes to aid in site selection are in place, but this is generally not presented by authors.

In Chapter 4 a method of network dimensioning was presented to provide an estimate of the number of sites required to meet the specified traffic demand. This chapter presents the next stage of the cell planning process. Algorithms are presented that make advantageous selections of sites from the candidate set with the aim of reducing the network's average cell load and network overloading. Specifically, a number of contributions to the field of automated cell planning are made including

- the presentation of the next stage in the proposed cell planning process (site selection optimisation);
- the proposal and comparison of three site selection algorithms;

- an analysis of the effects of the proposed site selection algorithms with regard to the UMTS network model presented in Chapter 3;
- an analysis of the effects of the proposed site selection algorithms for the different traffic scenarios presented in Chapter 3.

5.1 Site selection algorithms

The number of sites required is determined by the network dimensioning process presented in Chapter 4. The second stage of cell planning process is concerned with which sites are selected from the set of candidate sites for configuration and deployment. Due to the lack of deployment costs associated with each site, it is assumed that all sites in the candidate set are affordable if deployed. This chapter presents three algorithms for site selection service-potential-random, service-potential-deterministic and pattern-approximation.

Making site selections that consider the operational situation between the network design and the traffic scenario provides the impetus for the development of both service-potential-random and service-potential-deterministic algorithms. Both these algorithms involve selecting sites at locations where there is high local traffic demand. Differing slightly in design, service-potential-random provides a stochastic approach to site selection and contrasts with the deterministic approach of the service-potential-deterministic algorithm.

Previously, authors have placed sites at locations determined by a specified regular pattern. Although often used, this approach is far from practical as in a real world situation acquiring real estate at site locations pertaining to a pattern is difficult. Motivated by the difficulties in finding exact site locations and taking a practical approach to network design a pattern-approximation algorithm is developed. This algorithm involves selecting the estimated number of sites from the candidate set according to how well each site approximates a point belonging to a pre-specified pattern. In a real world scenario this could involve finding suitable approximations to patterns derived from legacy networks, hexagonal or regular placements, or areas where it is inexpensive to acquire site locations.

The proposed algorithms are presented in more detail in the following sections. Subsequently, experimentation is undertaken to determine which site selection algorithm is the most suitable in a number of different operational situations.

5.1.1 RANDOM

The number of sites required (specified at the network dimensioning stage) are selected from the candidate set of sites at random for configuration and deployment; for the remainder of the thesis the estimated number of sites, as calculated by the network dimensioning process presented in Chapter 4, is denoted E. If E is greater than the total number of sites in the candidate set then all sites in the candidate site are selected. Otherwise E sites are selected from the set of candidate sites at random and are then deployed as a start to the network design. For experimentation purposes all the selected sites in the network design are configured with either one omnidirectional antenna or three directional antennas, resulting in the network design having either all omnidirectional antennas or all directional antennas. Each antenna has the default configuration specified in Chapter 4. An example of random site selection can be seen in Figure 5.1.

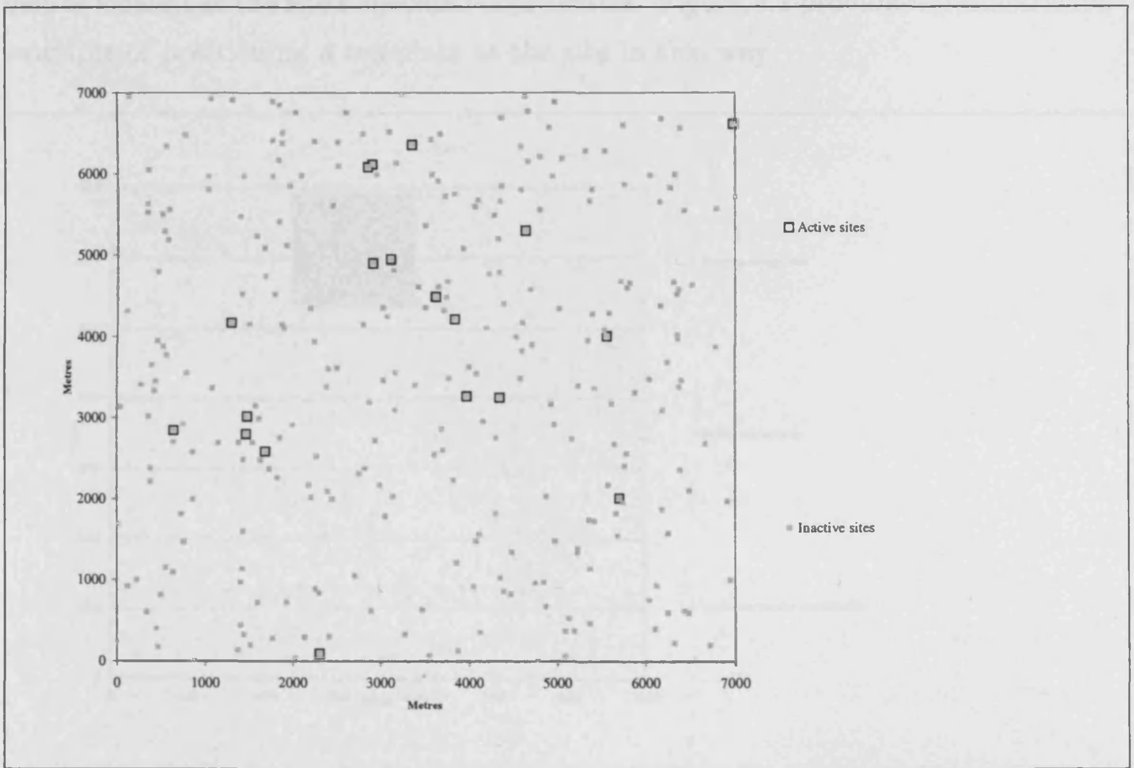


Figure 5.1: Illustrative example of random site selection made on the KORNET1 data set

5.1.2 SERVICE-POTENTIAL-RANDOM

E sites are selected from the candidate set by choosing those sites that have the potential to serve the most mobile station users. If a network design had been established, pilot power calculations followed by uplink and downlink load factor calculations would be carried out to determine the number of mobile station users that can be supported by each cell. However, as the network design is in the process of being established, these calculations cannot yet be carried out. Instead the cell area can be approximated and the sites that are likely to supply the most mobile station users can be found. An approximation of a cell's coverage area is found by placing a template over the site whose area is calculated by use of the following formula:

$$\text{area of the template} = \frac{M \text{ in sq. km}}{E}$$

allowing a template to be placed over a randomly selected site, with the template's centre located at the site's specified coordinates. Figure 5.2 provides an illustrative example of positioning a template at the site in this way.

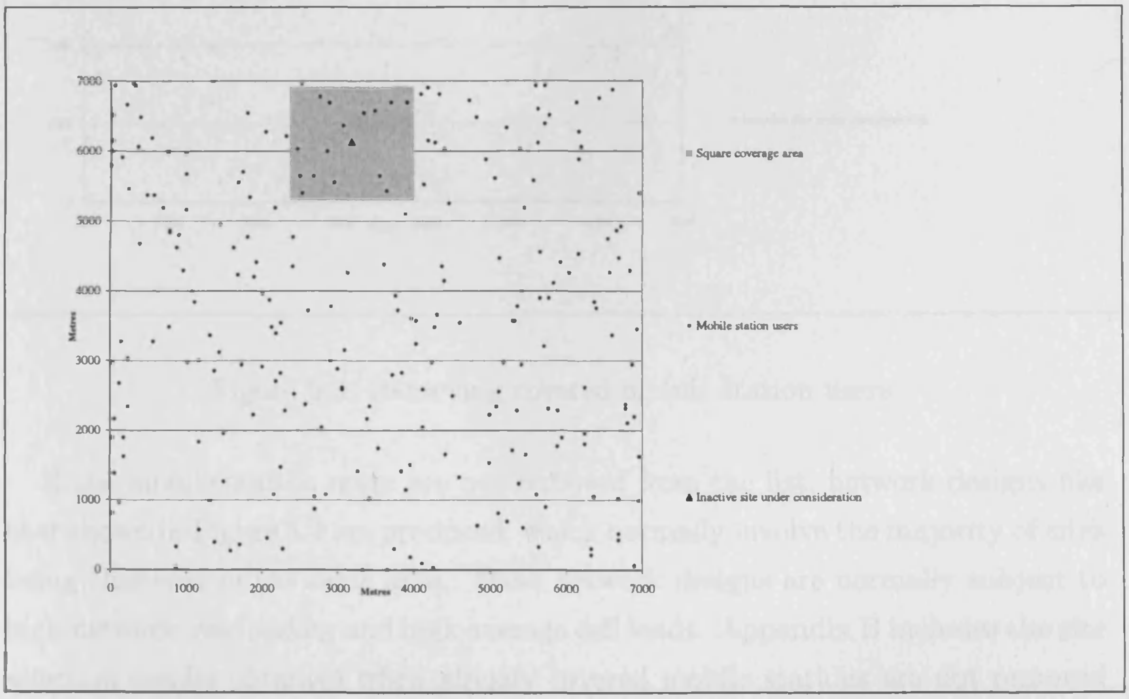


Figure 5.2: Example of cell area approximation

After the cell area is approximated the mobile station users covered by the cell can be determined. When a mobile station is classified as covered it no longer needs to be considered for coverage by any other site and can be removed from the list of uncovered mobile station users. Figure 5.3 provides an example where the mobile station users covered by the selected site have been removed from the list of uncovered mobile stations and are therefore not displayed in the illustration. The process of approximating a site's coverage area is repeated for all sites in the candidate set and the mobile station users covered by each cell are subsequently removed removed from the list.

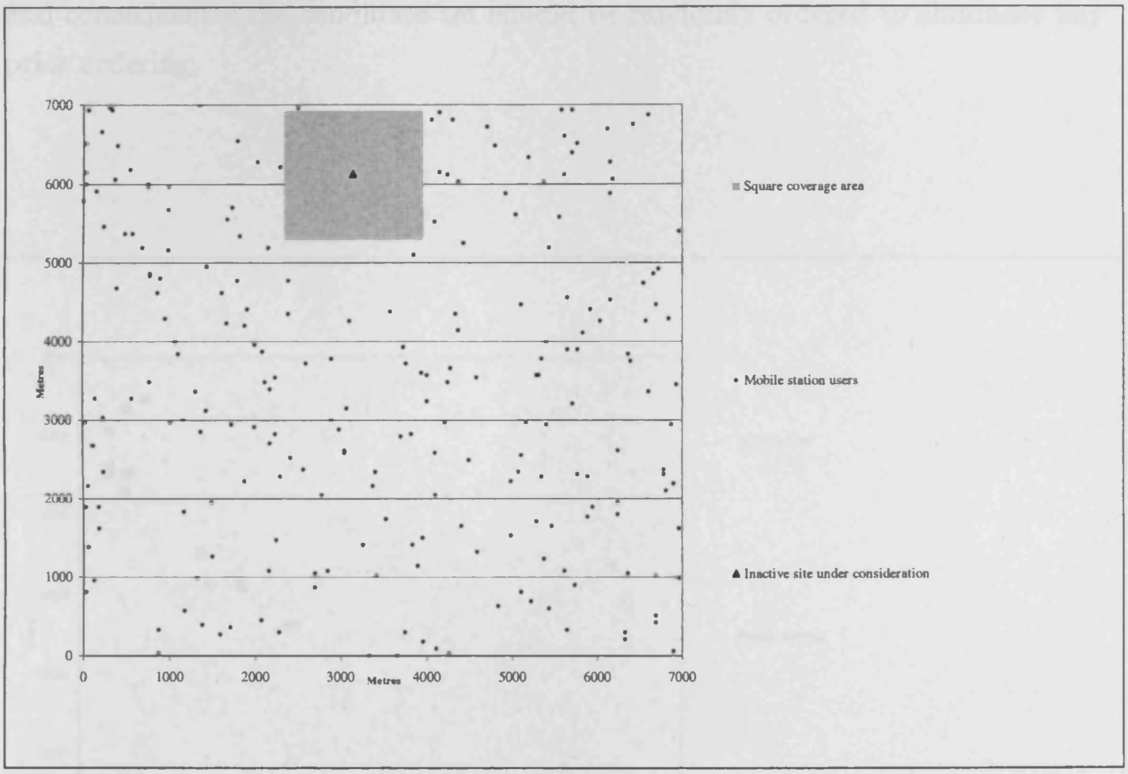


Figure 5.3: Removing covered mobile station users

If the mobile station users are not removed from the list, network designs like that shown in Figure 5.4 are produced, which normally involve the majority of sites being clustered in the same area. These network designs are normally subject to high network overloading and high average cell loads. Appendix B includes the site selection results obtained when already covered mobile stations are not removed from the list.

Finally, a list of candidate sites with their corresponding mobile station coverage totals can then be made allowing the E highest loaded sites to be selected for deployment. Figure 5.5 illustrates the sites selected when the service-potential-random algorithm is used for site selection within uniformly-random traffic scenario. Algorithm 5.1 provides pseudo-code for the service-potential-random algorithm.

When applying this algorithm the sooner a site is selected to have its cell coverage area approximated the more likely it is to cover a significant amount of traffic in the local area. Therefore the algorithm is dependent on the order of selections and consequently the candidate set should be randomly ordered to eliminate any prior ordering.

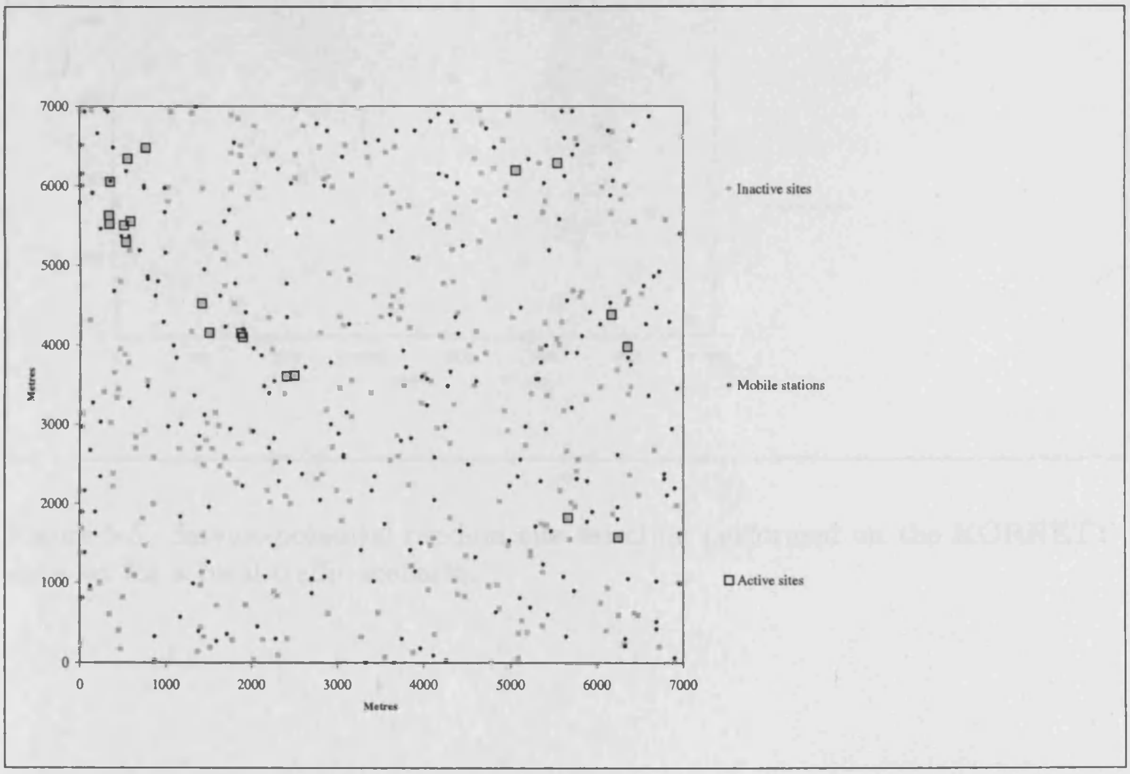


Figure 5.4: Site selections made when mobile stations that are covered are not removed.

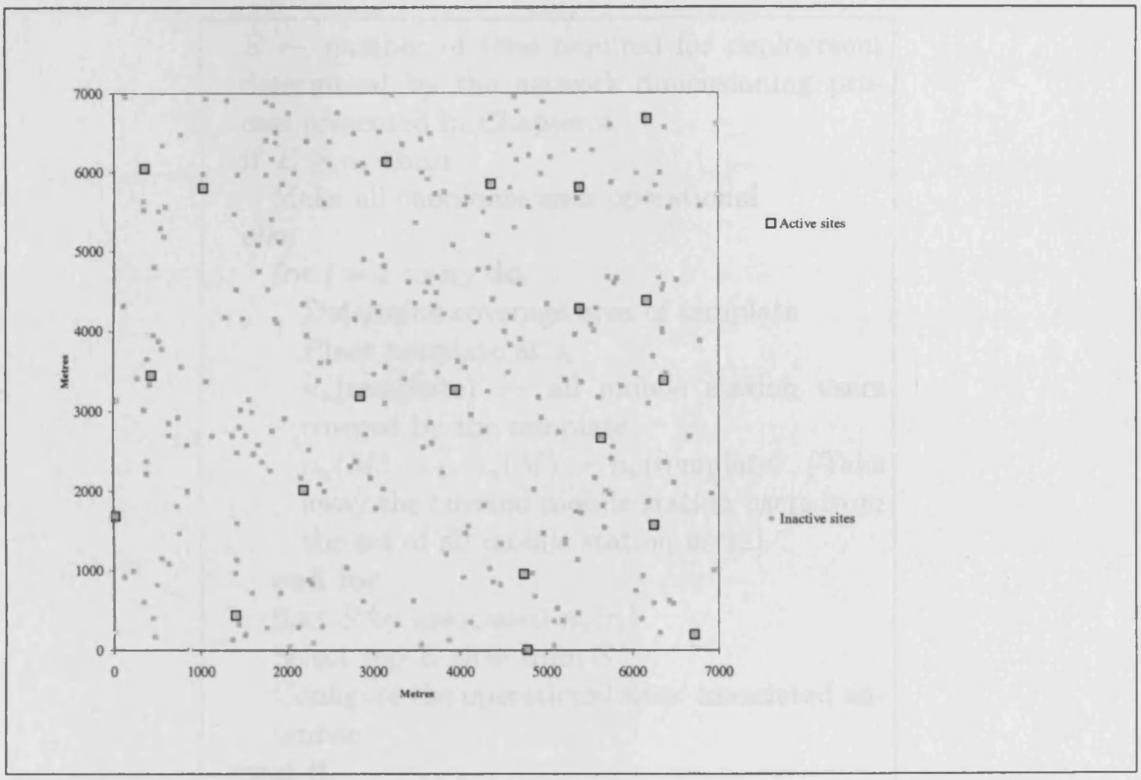


Figure 5.5: Service-potential-random site selection performed on the KORNET1 data set for a rural traffic scenario.

```
E ← number of sites required for deployment
determined by the network dimensioning pro-
cess presented in Chapter 4.
if E ≥ n_s then
  Make all candidate sites operational
else
  for i = 1 to n_S do
    Determine coverage area of template
    Place template at s_i
    n_u(template) ← all mobile station users
    covered by the template
    n_u(M) ← n_u(M) − n_u(template) {Take
    away the covered mobile station users from
    the set of all mobile station users}
  end for
  Sort S by associated n_u(r_i)
  Select top E sites from S
  Configure the operational sites' associated an-
  tennae
end if
```

Algorithm 5.1: Pseudo-code for service-potential-random algorithm

5.1.3 Service-potential-deterministic

Similar to the service-potential-random algorithm, a site's coverage area is approximated and the mobile station users that are covered by that site are determined but not removed from the list of uncovered mobile stations. The algorithm continues by approximating the cell area for each site and determining the users covered.

Instead of selecting the E sites that cover the most mobile stations from this list, only the site that covers the greatest number of mobiles is selected. Irrespective of which site's coverage area is first approximated the site that covers the most mobile stations, and it therefore regarded as the best, is selected at each iteration making this algorithm deterministic.

In a similar manner to the service-potential-random algorithm the mobile stations that are covered by the selected site are removed from the list of uncovered users. The whole process is then repeated until E sites are selected. Figure 5.6 illustrates the sites selected when this technique is used. Algorithm 5.2 provides pseudo-code for the service-potential-deterministic algorithm.

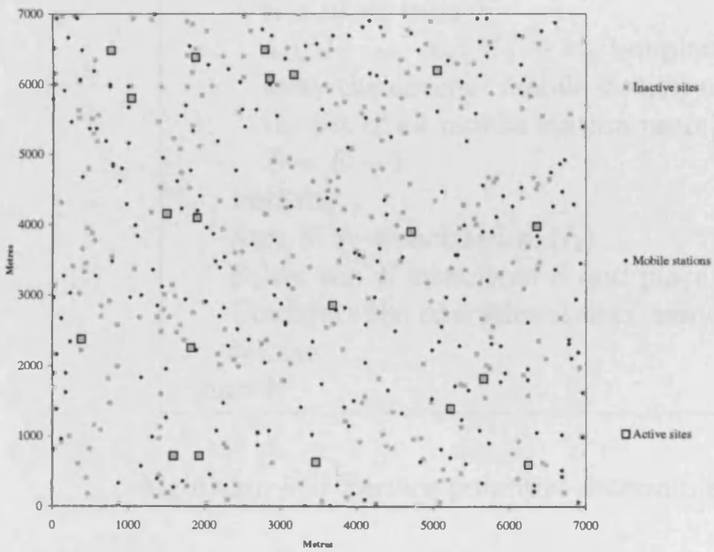


Figure 5.6: Site selections made by performing service-potential-deterministic on the KORNET1 network data set for rural traffic scenario

$E \leftarrow$ number of sites required for deployment determined by the network dimensioning process in 4.
if $E \geq n_s$ **then**
  Make all candidate sites operational
else
  for 1 to E **do**
    for $i = 1$ to n_S **do**
      Determine coverage area of the template
      Place the template at s_i
      n_u(template) $\leftarrow$ all mobile station users covered by the template
    end for
    Sort S in descending order of $n_u(c_k)$
    Select site that covers the most mobile station users from S
    $n_u(M) \leftarrow n_u(M) - n_u$(template) {Take away the covered mobile station users from the set of all mobile station users}
    $E = E - 1$
  end for
  Sort S by associated $n_u(r_i)$
  Select top E sites from S and place in N
  Configure the operational sites' associated antennae
end if

Algorithm 5.2: Service-potential-deterministic algorithm

5.1.4 Pattern-approximation

Sites are selected from the candidate set according to how closely each site matches a particular point belonging to a user specified pattern. A hexagonal pattern is used for experimentation due to it being frequently applied as a means of selecting sites for cell planning purposes (*e.g.* [21, 34]). Figure 5.7 illustrates the desired site locations determined by the hexagonal pattern (the steps involved in producing the hexagonal pattern are explained in appendix C).

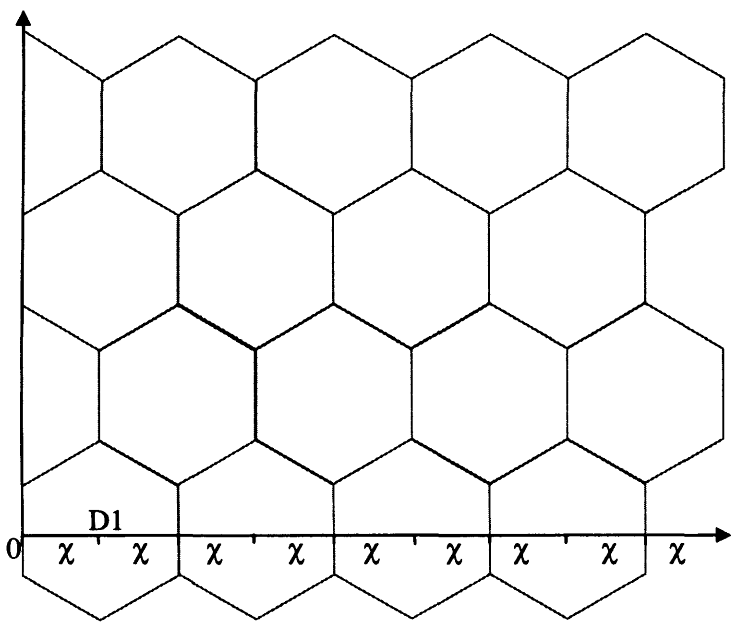


Figure 5.7: Hexagonal grid

If the operator has not provided a pattern to approximate but has specified that they would like to consider a regular pattern for site placement, such as a hexagonal pattern, a procedure has to be in place to find the pattern that has a similar number of points to that of E. In Figure 5.7 it can be seen that as χ (half the width of a hexagon) is increased the number of hexagons contained in the service area is reduced, likewise as χ is reduced the number of hexagons contained in the service area increases. In order to find the pattern with E sites or the pattern with the closest number of points to E, all patterns are found χ greater or equal to the loss interval of the service area (*i.e.* 30 metres for KORNET1 data set). For example, considering the KORNET1 data set with a loss interval of 30 metres, permitted lengths would be any multiple of 30 ranging from 30 to 7000 metres.

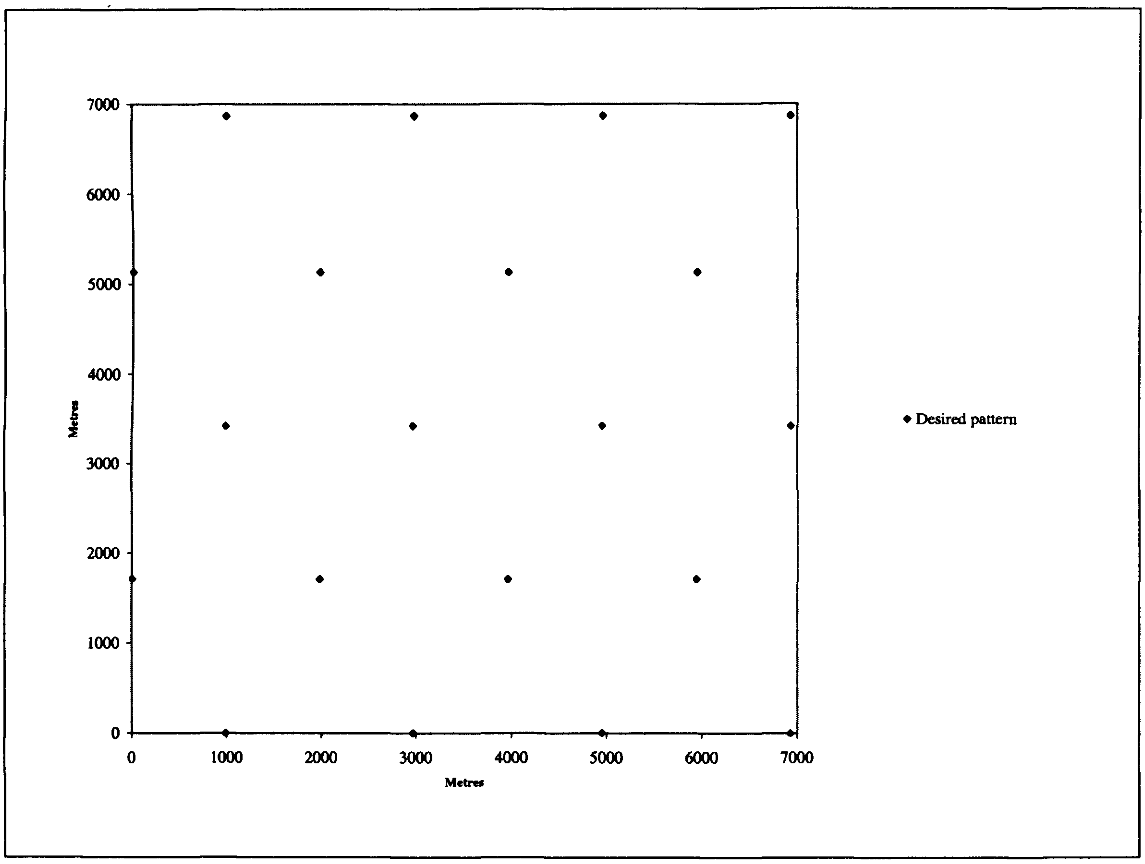


Figure 5.8: Illustration of desired site locations for a hexagonal pattern

When the pattern has been selected the set of points that form the selected pattern is defined

$$D = \{D_1, ..., D_{n_d}\}$$

and these points need to be matched to sites in the candidate set. Hence the distance between each desired site location (Figure 5.8) and each candidate site is calculated and recorded in a matrix. The candidate site that is closest in proximity to a desired point should then be selected, the row and column containing site and desired point can then be removed from the distance matrix. This process is then repeated selecting the best matched pair at each iteration until n_d sites are selected from S. Figure 5.9 illustrates the sites selected using the pattern-approximation algorithm, whilst pseudo-code is provided by algorithm 5.3.

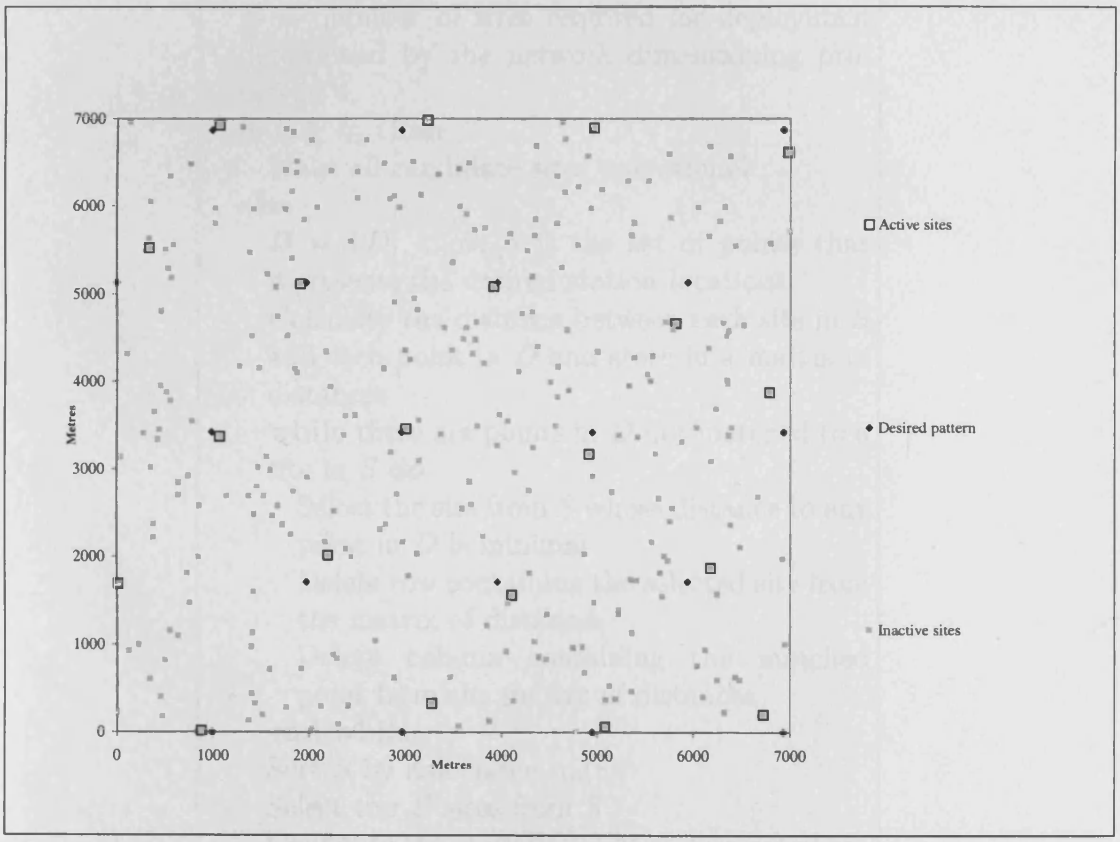


Figure 5.9: Site selections made by performing pattern-approximation on the KO-RNET1 data set for a rural scenario

$E \leftarrow$ number of sites required for deployment determined by the network dimensioning process in 4.
if $E \geq n_s$ **then**
  Make all candidate sites operational
else
  $D = \{D_1, ..., D_{n_d}\}$ is the set of points that represents the desired station locations
  Calculate the distance between each site in S and each point in D and store in a matrix of distances
  while there are points in D not matched to a site in S **do**
    Select the site from S whose distance to any point in D is minimal
    Delete row containing the selected site from the matrix of distances
    Delete column containing the matched point from the matrix of distances
  end while
  Sort S by associated $n_u(r_i)$
  Select top E sites from S
  Configure the operational sites' associated antennae
end if

Algorithm 5.3: Pseudo-code for pattern- approximation algorithm

5.2 RESULTS

The site selection stage of the proposed network dimensioning process is concerned with how the estimated number of sites, E, are selected from the set of candidate sites. In general each of the algorithms presented can be used to select E sites from the candidate set for deployment. The only exception to this is situations where a pattern containing exactly E desired site locations cannot be found. This can be viewed as a limitation of the pattern-approximation algorithm and causes difficulty when trying to compare this to the other proposed site selection algorithms. To allow a fair comparison of all algorithms it is important that the same number of sites are selected by each algorithm. This involves each algorithm selecting a number of sites by either *stepping-up* or *stepping-down* to the pattern that contains the same number or nearest number of desired site locations to that of E. Thus for testing purposes the number of sites for selection is determined by the pattern-approximation algorithm. Figure 5.10 and Figure 5.11 provide examples of when the estimate E, in this case 101 sites, cannot be matched to the magnitude of a pattern and it is necessary to step-down or step-up.

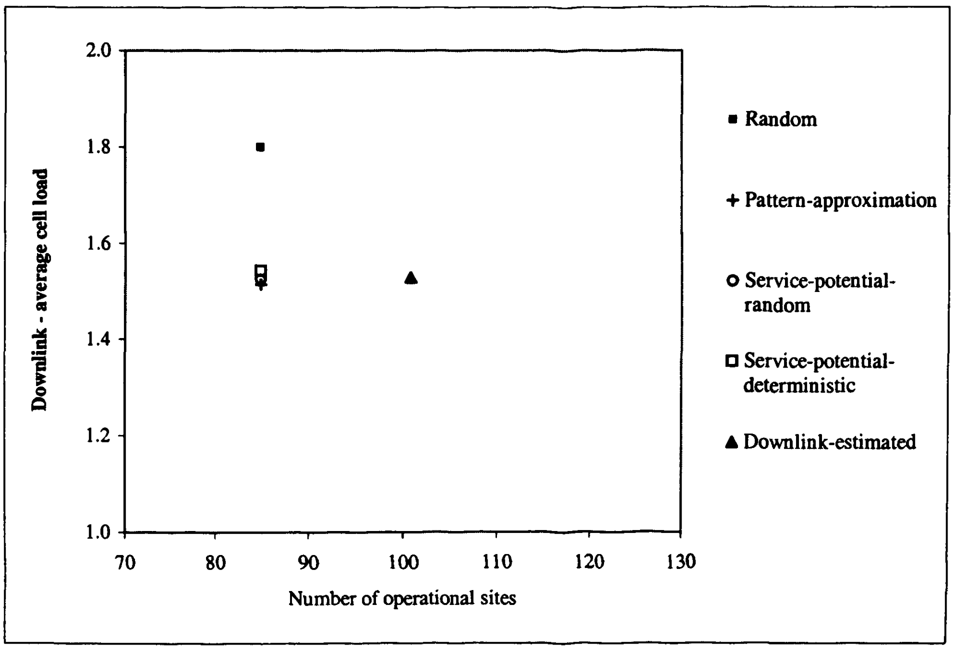


Figure 5.10: Stepping down to the nearest pattern

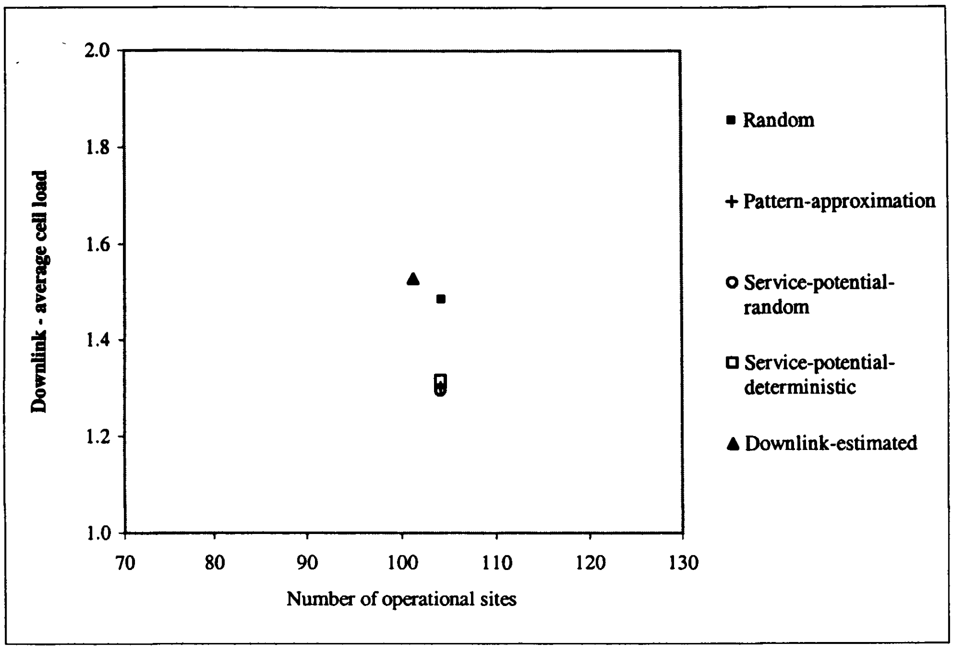


Figure 5.11: Stepping up to the nearest pattern

5.2.1 UNIFORMLY DISTRIBUTED TRAFFIC AND SITES

Results indicate that the use of service-potential-random, service-potential-deterministic and pattern-approximation algorithms for site selection can help produce a nominal network design with better network capacity than network designs produced randomly. In all test cases concerning uniformly distributed sites and traffic, the results of which are presented in Tables 5.1, 5.2, 5.3 and 5.4 and can be summarised as follows

- Pattern-approximation algorithm produced results with the lowest average cell load and lowest network over-loading in 11 of the 24 tests.
- Service-potential-random algorithm produced results with the lowest average cell load and lowest network over-loading in 8 out of 24 tests.
- Service-potential-deterministic algorithm produced results with the lowest average cell load and lowest network over-loading in 4 out of 24 tests.
- Random-selection algorithm was consistently out performed by all three algorithms.

A_k	u_d	Alg	E	n_{op}^S	n_{op}	Max $\eta_{DL}(c_k)$	Min $\eta_{DL}(c_k)$	Mean $\eta_{DL}(c_k)$	STDEV $\eta_{DL}(c_k)$	Network $\eta_{DL}(c_k)$	Des	Over	Under	Total over $d+m$
Omni	Rur	p-a	20	20	20	1.3168	0.1161	0.6374	0.3043	12.7479	2	3	15	2.4267
		s-p-r	20	20	20	1.9079	0.2133	0.7311	0.3845	14.6210	2	4	14	4.6182
		s-p-d	20	20	20	1.6617	0.0556	0.7789	0.3634	15.5771	5	4	11	4.1555
		r-s	20	20	20	4.7686	0.0000	1.0841	0.6508	21.6819	1	9	10	11.0589
	Sub	p-a	101	85	85	4.5941	0.1262	1.5143	0.8121	128.7169	13	47	25	74.6588
		s-p-r	101	85	85	4.2900	0.1786	1.5243	0.8506	129.5677	15	46	24	74.9882
		s-p-d	101	85	85	3.7444	0.2080	1.5434	0.8933	131.1860	7	49	29	76.4540
		r-s	101	85	85	6.1144	0.0000	1.7996	1.1438	152.9643	8	43	34	102.4526
	Urb	p-a	182	168	168	4.4681	0.0331	1.5326	0.9123	257.4737	19	91	58	159.0220
		s-p-r	182	168	168	4.5788	0.0000	1.4884	0.8596	250.0461	20	89	59	147.6888
		s-p-d	182	168	168	5.3874	0.0139	1.5367	0.8964	258.1737	25	91	52	155.3785
		r-s	182	168	168	5.5027	0.0000	1.5797	1.0951	265.3813	15	84	69	170.7925
Dir	Rur	p-a	7	7	21	1.3877	0.1214	0.6738	0.3747	14.1500	3	1	17	3.1255
		s-p-r	7	7	21	1.8032	0.0851	0.5779	0.2941	12.1358	1	2	18	2.4099
		s-p-d	7	7	21	1.1518	0.0000	0.6219	0.4498	13.0599	4	2	15	2.8753
		r-s	7	7	21	4.0267	0.0000	0.9185	1.7070	19.2889	1	4	16	10.5998
	Sub	p-a	34	33	99	2.6282	0.0000	0.8158	0.4466	80.7594	14	20	65	28.8669
		s-p-r	34	33	99	3.1004	0.0000	0.9285	0.5384	91.9196	11	25	63	39.6546
		s-p-d	34	33	99	2.8517	0.1005	0.8356	0.4218	82.7215	15	25	59	29.1165
		r-s	34	33	99	6.6399	0.0000	1.1143	0.7593	110.3183	10	31	58	60.8129
	Urb	p-a	61	56	168	3.7110	0.0062	1.1609	0.6517	195.0322	25	62	81	98.5737
		s-p-r	61	56	168	3.6651	0.0000	1.1097	0.6161	186.4218	16	69	83	91.0515
		s-p-d	61	56	168	3.5240	0.0000	1.1290	0.6026	189.6770	17	72	79	92.0814
		r-s	61	56	168	7.3645	0.0000	1.2830	0.8326	215.5474	16	71	81	128.6948

Table 5.1: Results for KORNET1 data set, when stepping-down to the the nearest pattern, comparing the performance of the four site selection algorithms: random selection (r-s), pattern-approximation (p-a) algorithm, service-potential-random algorithm (s-p-r), and service-potential-deterministic (s-p-d)

A_k	u_d	Alg	E	n_{op}^S	n_{op}	Max $\eta_{DL}(c_k)$	Min $\eta_{DL}(c_k)$	Mean $\eta_{DL}(c_k)$	STDEV $\eta_{DL}(c_k)$	Network $\eta_{DL}(c_k)$	Des	Over	Under	Total over $d+m$
Omni	Rur	p-a	20	20	20	1.3168	0.1161	0.6374	0.3043	12.7479	2	3	15	2.4267
		s-p-r	20	20	20	1.9079	0.2133	0.7311	0.3845	14.6210	2	4	14	4.6182
		s-p-d	20	20	20	1.6617	0.0556	0.7789	0.3634	15.5771	5	4	11	4.1555
		r-s	20	20	20	4.7686	0.0000	1.0841	0.6508	21.6819	1	9	10	11.0589
	Sub	p-a	101	104	104	3.6456	0.0522	1.3023	0.7412	135.4431	18	37	49	71.7113
		s-p-r	101	104	104	4.4216	0.2129	1.2954	0.7291	134.7193	21	44	39	69.5530
		s-p-d	101	104	104	3.6549	0.0000	1.3165	0.7515	136.9202	24	40	40	72.5416
		r-s	101	104	104	4.8394	0.0000	1.4863	0.9332	154.5759	12	44	48	6.9659
	Urb	p-a	182	216	216	4.4770	0.0000	1.1580	0.7025	250.1177	34	71	111	134.2293
		s-p-r	182	216	216	3.8377	0.0000	1.1564	0.6779	249.7753	36	73	107	129.1354
		s-p-d	182	216	216	4.3188	0.0000	1.1437	0.6616	247.0498	32	68	116	127.6532
		r-s	182	216	216	5.2600	0.0000	1.1901	0.7471	257.0610	31	70	115	143.9272
Dir	Rur	p-a	7	7	21	1.3877	0.1214	0.6738	0.3747	14.1500	3	1	17	3.1255
		s-p-r	7	7	21	1.8032	0.0851	0.5779	0.2941	12.1358	1	2	18	2.4099
		s-p-d	7	7	21	1.1518	0.0000	0.6219	0.4498	13.0599	4	2	15	2.8753
		r-s	7	7	21	4.0267	0.0000	0.9185	1.7070	19.2889	1	4	16	10.5998
	Sub	p-a	34	38	114	2.5512	0.0000	0.7492	0.4025	85.4121	14	16	84	26.8473
		s-p-r	34	38	114	3.1803	0.0000	0.8211	0.4581	93.6058	15	22	77	35.2925
		s-p-d	34	38	114	2.8030	0.0060	0.8166	0.4084	93.0930	15	25	74	31.3900
		r-s	34	38	114	5.7649	0.0000	0.9966	0.6958	113.6113	11	30	73	61.1742
	Urb	p-a	61	67	201	3.4295	0.0190	0.9336	0.5211	187.6579	22	54	125	79.7579
		s-p-r	61	67	201	4.0658	0.0000	1.0078	0.5696	202.5617	22	71	108	93.0354
		s-p-d	61	67	201	4.4619	0.0000	0.9936	0.5426	199.7150	29	60	112	88.0604
		r-s	61	67	201	7.1039	0.0000	1.1444	0.7926	230.0255	19	67	115	131.7425

Table 5.2: Results for KORNET1 data set, when stepping-up to the nearest pattern, comparing the performance of the four site selection algorithms: random selection (r-s), pattern-approximation (p-a) algorithm, service-potential-random algorithm (s-p-r), and service-potential-deterministic (s-p-d)

A_k	u_d	Alg	E	n_{op}^{S}	n_{op}	Max $\eta_{DL}(c_k)$	Min $\eta_{DL}(c_k)$	Mean $\eta_{DL}(c_k)$	STDEV $\eta_{DL}(c_k)$	Network $\eta_{DL}(c_k)$	Des	Over	Under	Total over $d+m$
		p-a	41	38	38	1.7658	0.0800	0.7004	0.3417	26.6140	5	7	26	6.6464
		p-a-r	41	38	38	2.3575	0.1112	0.9137	0.4771	34.7198	5	8	25	12.1213
	Rur	p-a-d	41	38	38	1.9924	0.1458	0.8036	0.4074	30.5386	8	8	22	10.0336
		r-s	41	38	38	3.4439	0.0000	0.9294	0.5698	35.3172	3	10	25	15.0339
		p-a	206	168	168	3.6807	0.0723	1.5509	0.8608	260.5566	19	99	50	153.0567
		p-a-r	206	168	168	5.1077	0.1895	1.6472	0.9463	276.7228	21	94	53	170.4170
Omni	Sub	p-a-d	206	168	168	3.9413	0.0776	1.5313	0.8601	257.2656	30	85	53	151.1571
		r-s	206	168	168	6.9915	0.0000	1.6839	1.1320	282.8870	26	84	58	184.4149
		p-a	372	340	340	4.6974	0.0000	1.5484	0.8881	526.4642	42	186	112	317.4617
		p-a-r	372	340	340	4.8177	0.0201	1.5276	0.8839	519.3839	62	174	104	308.1459
	Urb	p-a-d	372	340	340	5.3777	0.0000	1.5771	0.9475	536.1987	52	179	109	330.2111
		r-s	372	340	340	7.7519	0.0000	1.5780	0.9756	536.5315	39	172	129	345.4157
		p-a	14	14	42	2.0647	0.0000	0.7039	0.4204	29.5641	4	4	34	10.3183
		p-a-r	14	14	42	1.7024	0.0000	0.6850	0.3733	28.7687	7	6	29	9.1079
	Rur	p-a-d	14	14	42	2.8445	0.0554	0.7454	0.8431	31.3053	4	8	30	10.0905
		r-s	14	14	42	2.3920	0.0043	0.7613	0.4941	31.9730	3	11	28	12.7564
		p-a	69	67	201	3.3561	0.0156	0.8839	3.1003	177.6610	27	42	132	68.2739
		p-a-r	69	67	201	3.2155	0.0000	0.9714	0.5654	195.2522	25	55	121	88.2920
Dir	Sub	p-a-d	69	67	201	3.7740	0.0000	0.9512	0.5164	191.1827	28	53	120	78.0151
		r-s	69	67	201	5.1838	0.0000	1.0643	0.8134	213.9317	15	57	129	119.1792
		p-a	125	120	360	4.0231	0.0000	1.0542	0.5885	379.5093	60	113	187	172.6373
		p-a-r	125	120	360	4.4026	0.0000	1.0999	0.6160	395.9685	45	137	178	188.8625
	Urb	p-a-d	125	120	360	3.3646	0.0000	1.0827	0.5882	389.7668	62	124	174	175.6093
		r-s	125	120	360	6.1499	0.0000	1.2224	0.8635	440.0635	37	119	204	253.1735

Table 5.3: Results for KORNET2 data set, when stepping-down to nearest pattern, comparing the performance of the four site selection algorithms: random selection (r-s), pattern-approximation (p-a) algorithm, service-potential-random algorithm (s-p-r), and service-potential-deterministic (s-p-d)

A_k	u_d	Alg	E	n_{op}^S	n_{op}	Max $\eta_{DL}(c_k)$	Min $\eta_{DL}(c_k)$	Mean $\eta_{DL}(c_k)$	STDEV $\eta_{DL}(c_k)$	Network $\eta_{DL}(c_k)$	Des	Over	Under	Total over $d+m$
Omni	Rur	p-a	41	42	42	1.7780	0.0746	0.6430	0.3221	27.0080	3	8	31	5.9457
		s-p-r	41	42	42	1.8453	0.1119	0.8293	0.4311	34.8316	5	7	30	10.8340
		s-p-d	41	42	42	1.7210	0.0151	0.6910	0.3198	29.0218	2	8	32	6.8768
		r-s	41	42	42	3.5204	0.0000	0.8808	0.5506	36.9927	6	7	29	15.3832
	Sub	p-a	206	216	216	5.1590	0.0000	1.3049	0.7421	281.8547	31	93	92	153.4171
		s-p-r	206	216	216	4.2513	0.0446	1.3207	0.7552	285.2762	30	91	95	154.7750
		s-p-d	206	216	216	4.6870	0.0000	1.2270	0.6974	265.0339	32	83	101	135.6821
		r-s	206	216	216	4.6369	0.0000	1.3364	0.8140	288.6558	34	85	97	168.6150
	Urb	p-a	372	460	460	5.5304	0.0000	1.1602	0.6762	533.6751	77	145	238	274.0614
		s-p-r	372	460	460	5.1751	0.0000	1.1393	0.6589	524.0915	71	132	257	265.3668
		s-p-d	372	460	460	5.0848	0.0000	1.1256	0.6649	517.7851	69	136	255	261.0823
		r-s	372	460	460	5.7162	0.0000	1.1085	0.6834	509.9244	71	129	260	269.3175
Dir	Rur	p-a	14	14	42	2.0647	0.0000	0.7039	0.4204	29.5641	4	4	34	10.3183
		s-p-r	14	14	42	1.7024	0.0000	0.6850	0.3733	28.7687	7	6	29	9.1079
		s-p-d	14	14	42	2.8445	0.0554	0.7454	0.8431	31.3053	4	8	30	10.0905
		r-s	14	14	42	2.3920	0.0043	0.7613	0.4941	31.9730	3	11	28	12.7564
	Sub	p-a	69	80	240	2.2761	0.0000	0.7798	0.4266	187.1613	28	44	168	62.8039
		s-p-r	69	80	240	3.1773	0.0000	0.8485	0.4874	203.6376	30	42	168	78.6389
		s-p-d	69	80	240	2.6655	0.0000	0.8143	0.7414	195.4383	32	49	159	64.4202
		r-s	69	80	240	5.5506	0.0000	0.9332	0.7028	223.9669	20	59	161	115.1224
	Urb	p-a	125	143	429	3.5240	0.0000	0.9322	0.5269	399.8971	51	106	272	164.7148
		s-p-r	125	143	429	3.8924	0.0000	0.9655	0.5201	414.2024	57	136	236	171.5404
		s-p-d	125	143	429	3.1455	0.0000	0.9266	0.5015	397.5325	70	113	246	161.6350
		r-s	125	143	429	6.6000	0.0000	1.0619	0.7432	455.5464	44	113	272	238.0771

Table 5.4: Results for KORNET2 data set, when stepping-up to the nearest pattern, comparing the performance of the four site selection algorithms: random selection (r-s), pattern-approximation (p-a) algorithm, service-potential-random algorithm (s-p-r), and service-potential-deterministic (s-p-d)

Site density

As stated previously, when the number of sites estimated does not match any pattern found, a decision is made to step-up or step-down to the pattern with the number of desired points closest to E. In some cases results showed the same site selection algorithm produced the best performance irrespective of whether the decision to step-up or step-down was taken. This is observed for KORNET1 and KORNET2 results when sites are sectorized, within a suburban environment, as shown in Table 5.1 and Table 5.2.

In some cases stepping-up to the nearest pattern showed one algorithm to be the best for reducing average cell load and network over-loading, whilst stepping-down indicated another as the best. For an example compare entries in Table 5.1 and Table 5.2 for a network with sites having omnidirectional antenna within a suburban environment. In this case stepping-down results in the service-potential-random algorithm as the most effective, whilst stepping-up favoured the pattern-approximation algorithm. These results suggest that the estimated number of sites required for deployment affects which selection algorithm has the best performance.

To further confirm these results the pattern-approximation algorithm is consistently the best algorithm for KORNET1 and KORNET2 data sets for a rural user density when sites have a single omnidirectional antenna. However, when sites are sectorized the service-potential-random algorithm produces the best performance. This is likely to be the result of there being too few sites available to form a recognizable regular pattern. This leads to the conclusion that the pattern-approximation algorithm is most effective for a certain range of estimates.

Best performance

Table 5.5 provides a summary of the best-performing algorithms for each operational situation considered with the KORNET1 and KORNET2 data sets. By looking at the entries in Table 5.5 for KORNET1 it is seen that the pattern-approximation algorithm has the best performance when the number of candidate sites is between 20 and 85 (approximately 7% to 28% of candidate sites). Moreover, for KORNET2, pattern-approximation algorithm performs best when the E is between 38 and 360 (approximately 5.5% to 51%). From analysis of these results it is

A_k	u_d	Alg	n_{op}^S	n_{op}	Max $\eta_{DL}(c_k)$	Min $\eta_{DL}(c_k)$	Mean $\eta_{DL}(c_k)$	STDEV $\eta_{DL}(c_k)$	Network $\eta_{DL}(c_k)$	Des	Over	Under	Total over	Step $d+m$
Dir	Rur	s-p-r	7	21	1.8032	0.0851	0.5779	0.2941	12.1358	1	2	18	2.4099	up
Dir	Rur	s-p-r	7	21	1.8032	0.0851	0.5779	0.2941	12.1358	1	2	18	2.4099	down
Omni	Rur	p-a	20	20	1.2094	0.1834	0.6592	0.3142	13.1831	1	3	16	2.6848	down
Omni	Rur	p-a	20	20	1.3168	0.1161	0.6374	0.3043	12.7479	2	3	15	2.4267	up
Dir	Sub	p-a	33	99	2.6282	0.0000	0.8158	0.4466	80.7594	14	20	65	28.8669	down
Dir	Sub	p-a	38	114	2.5512	0.0000	0.7492	0.4025	85.4121	14	16	84	26.8473	up
Dir	Urb	s-p-r	56	168	3.6651	0.0000	1.1097	0.6161	186.4218	16	69	83	91.0515	down
Dir	Urb	p-a	67	201	3.4295	0.0190	0.9336	0.5211	187.6579	22	54	125	79.7579	up
Omni	Sub	p-a	85	85	4.5941	0.1262	1.5143	0.8121	128.7169	13	47	25	74.6588	down
Omni	Sub	s-p-r	104	104	4.4216	0.2129	1.2954	0.7291	134.7193	21	44	39	69.5530	up
Omni	Urb	s-p-r	168	168	4.5788	0.0000	1.4884	0.8596	250.0461	20	89	59	147.6888	down
Omni	Urb	s-p-d	216	216	4.3188	0.0000	1.1437	0.6616	247.0498	32	68	116	127.6532	up
Dir	Rur	s-p-r	14	42	1.7024	0.0000	0.6850	0.3733	28.7687	7	6	29	9.1079	up
Dir	Rur	s-p-r	14	42	1.7024	0.0000	0.6850	0.3733	28.7687	7	6	29	9.1079	down
Omni	Rur	p-a	38	38	1.7658	0.0800	0.7004	0.3417	26.6140	5	7	26	6.6464	down
Omni	Rur	p-a	42	42	1.7780	0.0746	0.6430	0.3221	27.0080	3	8	31	5.9457	up
Dir	Sub	p-a	67	201	3.3561	0.0156	0.8839	3.1003	177.6610	27	42	132	68.2739	down
Dir	Sub	p-a	80	240	2.2761	0.0000	0.7798	0.4266	187.1613	28	44	168	62.8039	up
Dir	Urb	p-a	120	360	4.0231	0.0000	1.0542	0.5885	379.5093	60	113	187	172.6373	down
Dir	Urb	s-p-d	143	429	3.1455	0.0000	0.9266	0.5015	397.5325	70	113	246	161.6350	up
Omni	Sub	s-p-d	168	168	3.9413	0.0776	1.5313	0.8601	257.2656	30	85	53	151.1571	down
Omni	Sub	s-p-r	216	216	4.6870	0.0000	1.2270	0.6974	265.0339	32	83	101	135.6821	up
Omni	Urb	s-p-r	340	340	4.8177	0.0201	1.5276	0.8839	519.3839	62	174	104	308.1459	down
Omni	Urb	r-s	460	460	5.7162	0.0000	1.1085	0.6834	509.9244	71	129	260	269.3175	up

Table 5.5: Best performing site selection algorithms for each operational scenario considered for both data sets.

recommended that the pattern-approximation algorithm is only used for site selection when the estimated number of sites for selection is between 5.5% and 51% of the total number of candidate sites. Future work in this area should involve more experimentation to further support the percentage range for which the pattern-approximation algorithm may be more suitable than the service-potential-random algorithm or the service-potential-deterministic algorithm.

The service-potential-random algorithm performs best when either very few or many sites are required for selection, but this may be due to the pattern-approximation algorithm not performing as well in those scenarios. In general the service-potential-random algorithm is consistently better than the service-potential-deterministic algorithm and requires less computation. Figure 5.12 provides an example of site selections made when applying these algorithms to a typical suburban user density scenario. The remainder of this section discusses a number of key observations made in the analysis of these results.

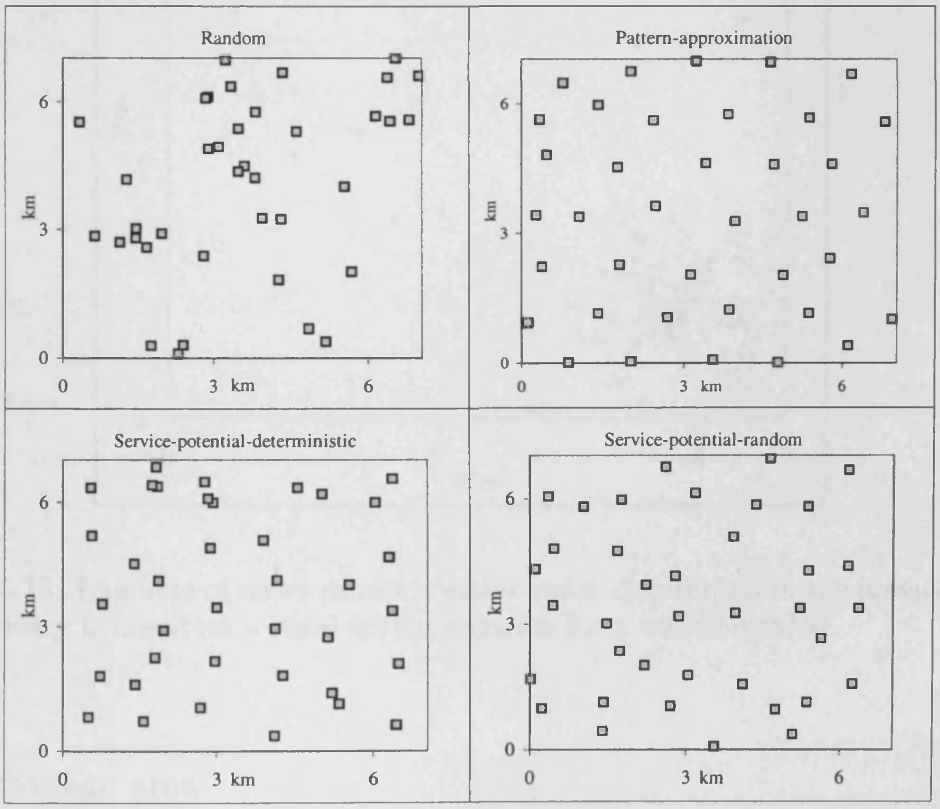


Figure 5.12: Illustration of site selections made when considering uniform traffic in a suburban environment

5.2.2 NON-UNIFORM TRAFFIC

In Section 5.2.1 uniformly distributed traffic was considered and results indicated that pattern-approximation and service-potential-random are suitable techniques for making site selections that reduce the average cell load and cell over-loading experienced in the network. This section investigates if consideration of non-uniform traffic scenarios (Figure 5.13) affects the site selection results.

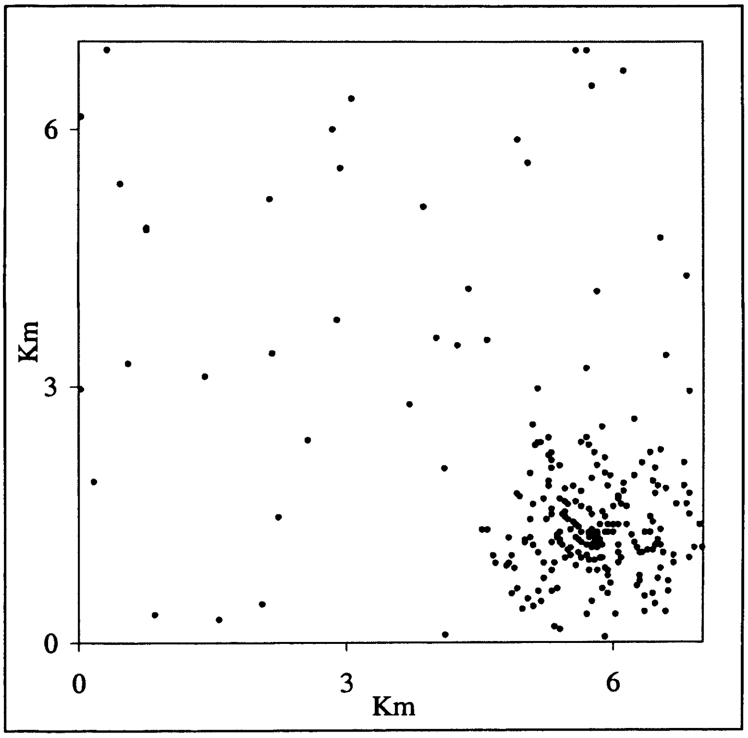


Figure 5.13: Example of users random-with-cluster distributed in the service area. User density is based on a rural traffic scenario for a mixed service

Cell coverage area

The size of the region used to approximate the cell area in both the service-potential-random and service-potential-deterministic algorithms is central to their performance. The method for calculating the area of the template was presented in Section 5.1.2 and this method was suitable for determining the approximation area when considering uniformly distributed mobile station users as it ensured that sites were distributed evenly across the service area. When users are not uniformly distributed a smaller approximation area is required to allow sites to be clustered in intense traffic areas.

Tests are undertaken for a non-uniform traffic scenario and consider three differently sized cell coverage areas for use in the service-potential-random and service potential-deterministic algorithms. Results presented in Table 5.6 indicate that a template with side set to 500 metres produces the most effective nominal network design having the lowest range of cell loads, the greatest number of cells with non-zero load and most cells classified as desired. 500 metres is less than half the length of a side that was used when traffic is uniformly distributed. The clustered quarter of the service area has approximately double the amount of traffic compared to the situation when traffic was uniformly distributed. Thus the average cell area has approximately the same amount of traffic in the clustered quarter as an average cell had when considering uniformly distributed traffic, making this cell area approximation the most suitable.

Best performance

Results displayed in Table 5.7 indicate that the random and pattern-approximation algorithms have the lowest average cell load and lowest network overloading, but the standard deviation of the cell loads is higher than service-potential-random and service-potential-deterministic algorithms.

Figure 5.14 presents two graphs that display the downlink load of each cell in a network design when selections are made using: service-potential-deterministic algorithm and pattern-approximation respectively. The downlink load of each cell appears to be spread more evenly amongst cells when selections are made using service-potential-deterministic. This is due to the selected sites being located within the cluster of users, whereas selections made using either the random or pattern-approximation algorithm allow selections in regions of the service area with less traffic demand as seen in Figure 5.15.

The service-potential-deterministic cell plan is clearly the more desirable in this situation as the load is shared amongst all cells in the network and is likely to

side	n_{op}^{S}	n_{op}	Max $\eta_{DL}(c_k)$	Min $\eta_{DL}(c_k)$	Mean $\eta_{DL}(c_k)$	STDEV $\eta_{DL}(c_k)$	Network $\eta_{DL}(c_k)$	Desired	Over	Under	Total over $d+m$
50	20	20	7.5284	0.0000	0.8268	1.0604	16.5364	0	3	17	13.3279
100	20	20	7.2385	0.0000	1.5633	1.0842	31.2652	3	9	8	21.5809
500	20	20	5.8258	0.0131	1.4187	0.8567	28.3737	3	8	9	17.6849

Table 5.6: Results for service-potential-deterministic when reducing the template's coverage area

provide a better initial network design from which to perform optimisations. When using non-uniform traffic the average cell load and total network over-loading can not be used as a measure of performance for the network design alone. Extra information should be considered to determine how good a cell plan is such as maximum, minimum and standard deviation of the cell loads.

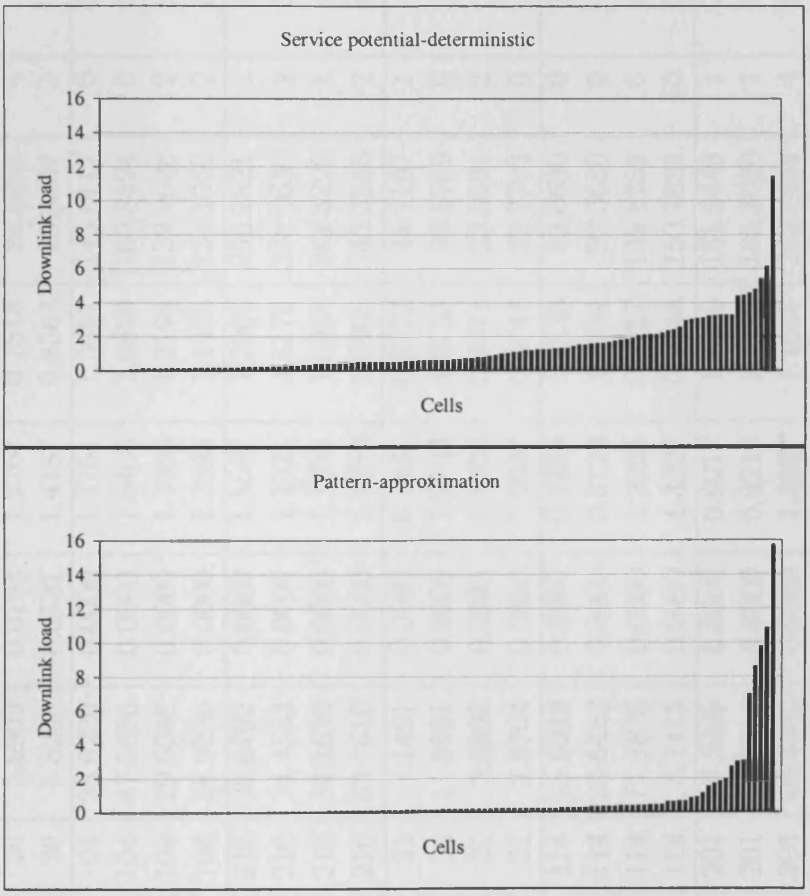


Figure 5.14: The two graphs displayed show the downlink load of each cell in a network design when selections are made using: service-potential-deterministic algorithm and pattern-approximation

A	u_d	Alg	n_{op}^S	n_{op}	Max $\eta_{DL}(c_k)$	Min $\eta_{DL}(c_k)$	Mean $\eta_{DL}(c_k)$	STDEV $\eta_{DL}(c_k)$	Network $\eta_{DL}(c_k)$	Des	Over	Under	Total over $d+m$
Omni	Rur	p-a	20	20	6.4471	0.0000	0.5468	1.1313	10.9355	0	4	16	8.5876
		r-s	20	20	8.7491	0.0000	0.4375	1.4940	8.7491	0	1	19	8.0891
		s-p-d	20	20	5.6909	0.0794	1.2267	0.7518	24.5335	4	6	10	13.5132
		s-p-r	20	20	5.8258	0.0131	1.4187	0.8567	28.3737	3	8	9	17.6849
	Sub	p-a	104	104	28.6220	0.0000	1.3751	1.6457	143.0117	0	17	87	132.5703
		r-s	104	104	47.5686	0.0000	1.5466	2.0869	160.8494	0	13	91	152.2129
		s-p-d	104	104	19.6048	0.0000	1.3385	1.2194	139.2028	2	28	74	119.5271
		s-p-r	104	104	18.9220	0.0000	1.2895	1.1495	134.1060	2	30	72	112.5250
	Urb	p-a	216	216	38.6792	0.0000	1.1587	1.2065	250.2821	1	40	175	190.9514
		r-s	216	216	24.4583	0.0000	1.1021	1.1176	238.0630	2	37	177	182.7746
		s-p-d	216	216	34.1530	0.0000	1.1335	1.0958	244.8299	1	42	173	185.2368
		s-p-r	216	216	33.7610	0.0000	1.1359	1.0805	245.3546	2	44	170	182.8878
Dir	Rur	p-a	7	21	7.1491	0.0000	0.7481	0.8722	15.7107	1	2	18	11.0682
		r-s	7	21	11.6891	0.0000	1.2703	1.3753	26.6769	0	4	17	22.3646
		s-p-d	7	21	3.5396	0.0883	1.1200	0.6871	23.5191	2	7	12	11.9161
		s-p-r	7	21	2.9704	0.0850	1.0847	0.6747	22.7793	0	7	14	10.8800
	Sub	p-a	38	114	15.6949	0.0000	0.7286	1.2538	83.0630	0	14	100	59.9384
		r-s	38	114	29.6422	0.0000	0.8129	1.4784	92.6680	0	9	105	70.9244
		s-p-d	38	114	11.3876	0.0000	1.2265	0.9757	139.8259	6	41	67	87.3084
		s-p-r	38	114	8.7415	0.0000	1.3227	0.9846	150.7830	10	39	65	95.1034
	Urb	p-a	67	201	19.2495	0.0000	0.9017	1.3299	181.2443	1	27	173	135.2463
		r-s	67	201	31.3811	0.0000	0.9219	1.7029	185.3020	1	18	182	139.6264
		s-p-d	67	201	16.4362	0.0000	1.3057	1.1927	262.4454	4	63	134	187.9878
		s-p-r	67	201	13.4254	0.0000	1.3376	1.1670	268.8619	7	67	127	184.6002

Table 5.7: Site selection is performed considering non-uniform traffic distributed using the random-with-cluster technique for rural and suburban scenarios

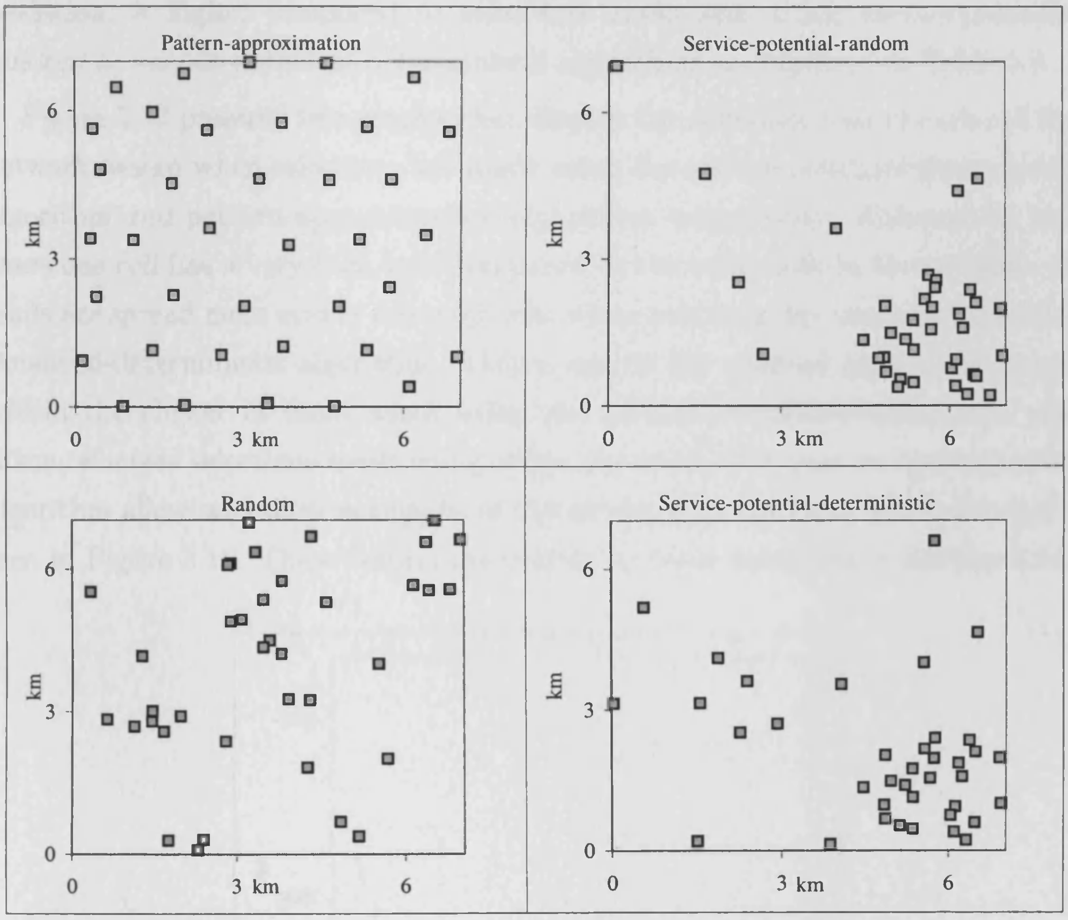


Figure 5.15: Site selections are made with non-uniform suburban traffic environment

5.2.3 NON-UNIFORMLY DISTRIBUTED TRAFFIC AND SITES

Site selection for non-uniformly distributed traffic and sites produces similar results to Section 5.2.2 when site selection is performed using pattern-approximation, service-potential-random, service-potential-deterministic and random algorithms. Results indicate that although random and pattern-approximation algorithms produce the lowest average cell load the range of cell loads, and hence the standard deviation, is higher compared to selections made with either service-potential-random or service-potential-deterministic algorithms as displayed in Table 5.8.

Figure 5.17 presents two graphs that display the downlink load of each cell in a network design when selections are made using the service-potential-deterministic algorithm and pattern-approximation algorithms respectively. Although in both cases one cell has a very high load compared to the other cells in the network, the loads are spread more evenly amongst cells when selections are made using service-potential-deterministic algorithm. This is due to the selected sites being located within the cluster of users when using the service-potential-deterministic algorithm, whereas selections made using either the random or pattern-approximation algorithm allow selections in regions of the service area with less traffic demand as seen in Figure 5.18. These results are similar to those presented in Section 5.2.2.

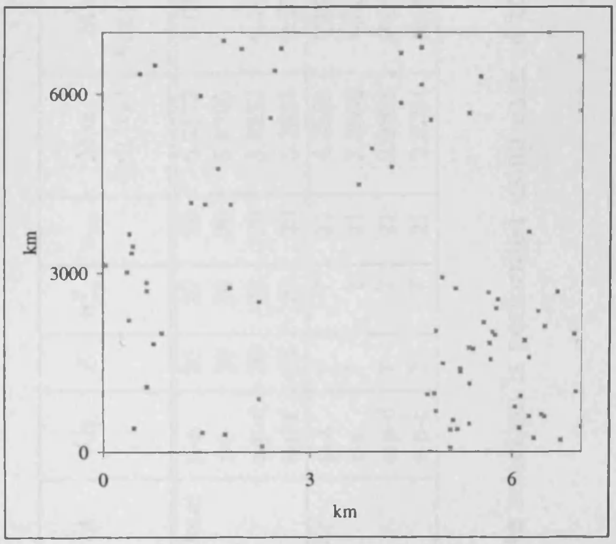


Figure 5.16: Non-uniformly distributed candidate sites

A	Alg	E	n_{op}^{S}	n_{op}	Max $\eta_{DL}(c_k)$	Min $\eta_{DL}(c_k)$	Mean $\eta_{DL}(c_k)$	STDEV $\eta_{DL}(c_k)$	Network $\eta_{DL}(c_k)$	Des	Over	Under	Total over $d+m$
Omni	p-a	20	20	20	6.2173	0.0144	0.6801	0.9033	13.6009	0	3	17	9.0978
	r-s	20	20	20	5.8295	0	0.9556	1.0274	19.1120	0	6	14	11.7721
	s-p-d	20	20	20	5.8352	0.1483	1.2444	0.7996	24.8875	1	7	12	13.8365
	s-p-r	20	20	20	5.3633	0.2743	1.3703	0.8510	27.4068	2	9	9	15.2820
Dir	p-a	7	7	21	4.3552	0.0000	0.6940	0.7613	14.5742	0	3	18	9.5868
	r-s	7	7	21	2.8802	0.0000	0.6433	0.6030	13.5091	0	5	16	6.8998
	s-p-d	7	7	21	2.9801	0.0168	0.9470	0.6032	19.8862	2	6	13	9.3561
	s-p-r	7	7	21	2.9704	0.0850	1.0847	0.6747	22.7793	0	7	14	10.8800

Table 5.8: Site selection is performed using each of the selection algorithms for non-uniformly distributed candidate sites and traffic

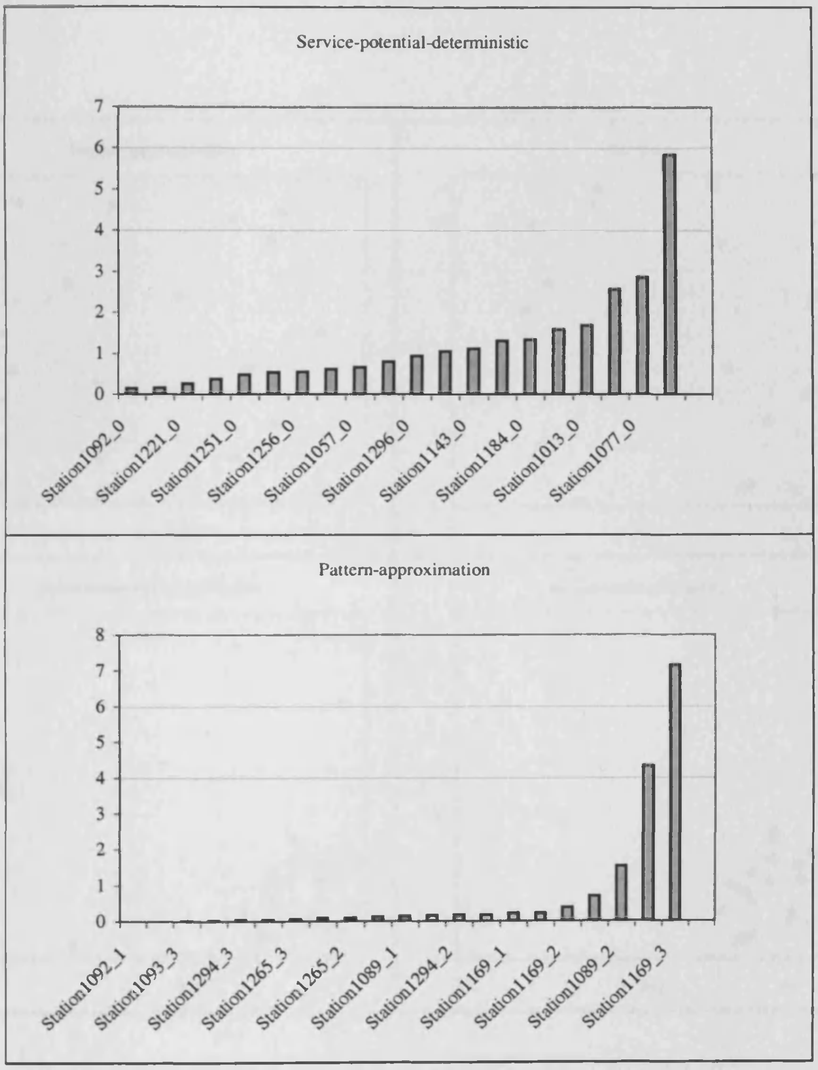


Figure 5.17: The two graphs displayed show the downlink load of each cell in a network design when selections are made using: service-potential-deterministic algorithm and pattern-approximation

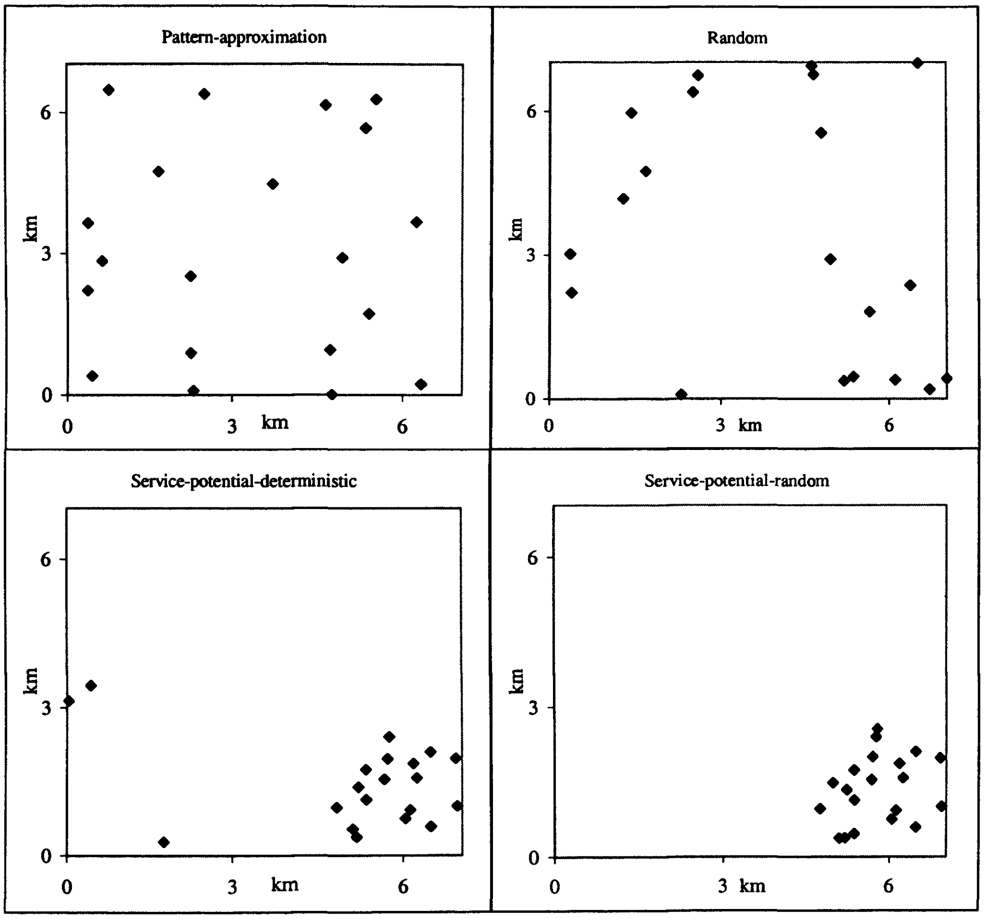


Figure 5.18: Illustration of site selections made when considering non-uniformly distributed traffic and candidate sites

5.2.4 PERFORMANCE OF RANDOM SELECTION

The performance of random site selection is affected by the magnitude of the set of candidate sites. When the candidate set is large the number of possible random network designs, with E sites, is much higher than the number of network designs that can be produced with a smaller set. Thus random selection with a smaller candidate set is more likely to select the same or very similar set of sites for deployment than those selected by the pattern-approximation, service-potential-random or service-potential-deterministic algorithms.

Results displayed in Table 5.9 support this conjecture, showing that when the size of the candidate set of sites is reduced to 200 sites, random selection performs more similarly to the performance of pattern-approximation and service-potential-deterministic, than when the candidate set size is 300 sites. In one case random selection is better than either the pattern-approximation or service-potential-random algorithms. A larger candidate set also provides more selection options when trying to match sites to a desired pattern and is likely to be useful when trying to select sites in high traffic areas.

A_k	u_d	Alg	n_{op}^S	n_{op} $\eta_{DL}(c_k)$	Max $\eta_{DL}(c_k)$	Min $\eta_{DL}(c_k)$	Mean $\eta_{DL}(c_k)$	STDEV $\eta_{DL}(c_k)$
Omni	Ru	p-a	22	22	1.7236	0	0.6201	0.4545
		s-p-r	22	22	1.9566	0.01117	0.7349	0.5756
		r-s	22	22	2.2058	0	0.7523	0.5069
	Sub	p-a	120	120	5.7200	0	0.8148	0.8185
		s-p-r	120	120	3.5004	0	0.7534	0.6191
		r-s	120	120	3.6515	0	0.7910	0.6878
	Urb	p-a	150	150	4.4325	0	1.2032	0.9041
		s-p-r	150	150	4.4325	0	1.2032	0.9041
		r-s	150	150	4.4325	0	1.2032	0.9041
Dir	Rur	p-a	9	27	3.1918	0	0.6469	0.9373
		s-p-r	9	27	5.6483	0	0.7800	1.3714
		r-s	9	27	3.0220	0	0.4795	0.7829
	Sub	p-a	42	126	9.2985	0	0.9451	1.6390
		s-p-r	42	126	8.3664	0	0.8111	1.4104
		r-s	42	126	8.8334	0	0.9261	1.5968
	Urb	p-a	80	240	9.3100	0	0.9622	1.7725
		s-p-r	80	240	15.1797	0	1.0608	2.1334
		r-s	80	240	10.0847	0	0.9934	1.8526

Table 5.9: Reducing the size of the candidate set

This leads to the conclusion that site selection relies on the candidate site density. The greater the candidate site density, the better the suggested algorithms are likely to perform and the more worthwhile it is to follow the suggested dimensioning procedure. With a reduced candidate site density the chance of pattern-approximation, service-potential-random and service-potential deterministic performing better than random selection is greatly reduced. Further research should concentrate on determining a site density that has to be met in order to deem the use of site selection techniques worthwhile.

5.3 SUMMARY

Overall results indicate that more sophisticated dimensioning techniques can improve initial site selection compared to random site selection. Algorithms have been presented such as service-potential-random, service-potential-deterministic and pattern-approximation that perform well and should be considered.

Performance of pattern-approximation is seemingly restricted to scenarios where the number of sites required for selection is approximately less than half of the candidate set and it is therefore recommended that the pattern-approximation algorithm is not used outside this range. Service-potential-random and service-potential-deterministic algorithms are typically subject to less constraints and variation in results than the pattern-approximation algorithm and experimentation showed that these algorithms are likely to produce better network designs when the traffic definitions are non-uniform. For non-uniform traffic scenarios the site estimates appear to be too high and this is a direct result of non-uniform loading of cells and non-uniform traffic distributions not being considered at the network dimensioning stage. Future work should concentrate on more effective modelling of the 3GSTART equations for non-uniform traffic scenarios.

Results highlight that the quantity and regularity of candidate sites affect dimensioning and this is largely dependent on the magnitude of the set of candidate sites. In some cases where the candidate set is small, performance of the proposed site selection algorithms approaches that of random site selection. Further research into the minimum size of the candidate set should be undertaken, specifying the requirement in terms of site density, which would allow the minimum candidate set size to be specified irrespective of the dimensions of the service area.

Future work could consider experimenting with different desired patterns for the pattern-approximation algorithm. The service-potential-random and service-potential-deterministic algorithms could be altered to use actual cell supply area calculations instead of making the less computationally intensive cell area approximations.

The first two stages of the proposed cell planning process is capable of producing a reasonable nominal network design, which can take the form of a stand-alone tool that provides an approximate guide of a network's infrastructure requirements for budgetary purposes. Site selection optimisation can be applied separately from network dimensioning if the operator has a fixed and specified number of sites required for deployment at the start of site selection optimisation. However, all the conclusions assume that each site in the network has the same configuration. It could be the case that if each site was individually configured conclusions could change. The remaining chapters consider the possible application of network dimensioning and site selection optimisation in automated cell planning to provide a suitable starting position for further network configuration optimisation.

CHAPTER 6

OPTIMISATION FRAMEWORK

An optimisation framework is proposed to allow an investigation into the effect of network dimensioning and site selection optimisation as a precursor to network configuration optimisation. Solution techniques can be applied to instances of the cell planning problem to aid the discovery of suitable network design solutions. This chapter looks specifically at building an optimisation framework that can use either local search or tabu search as the chosen solution technique and is organised into three main sections which include:

- Section 6.1 which defines the cost function, move strategies and presents the implementation of local search and tabu search heuristics used in this work;
- Section 6.2 determines, via a series of experiments, which heuristic is the most suitable at optimising the networks considered;
- Section 6.1.2 presents methods for tuning tabu search to allow application to a wide range of scenarios.

The customised optimisation framework is then used in Chapter 7 to test the proposed three stage cell planning solution.

6.1 HEURISTICS

Heuristics and meta-heuristics can be applied to instances of the cell planning problem to aid the discovery of suitable network design solutions. However, irrespective of which heuristic or meta-heuristic is used a cost function has to be defined which provides a measure of performance for a candidate network. The cell planning problem has often been classified as a multi-objective problem as discussed in Chapter 3. These multiple objectives are likely to be inter-related or conflicting and need to be considered simultaneously. One approach to evaluating a network design that requires multiple objectives to be optimised involves translating the multi-objective problem into a more manageable format so that algorithms suitable for solving single objective problems may be applied. The *weighted* approach is popular for converting multi-objective problems into single objective problems [42, 47]. In this work a weighted additive objective function is used. The cost function is formed using a linear combination of the individual components:

$$e = \sum_n e_n \tag{6.1}$$

where e_n is the cost of component n and includes its associated weight w_n. The weight indicates the relative importance of the nth objective and is specified for each of the objectives before the optimisation begins. The cost function can incorporate many objectives and measures that are considered suitable in evaluating the state of a network design. The components of the cost function used here are:

- The range of uplink cell loads

$$e_0 = w_0 \left(\max_{k=0}^{n_{op}} \eta_{UL}(c_k) - \min_{k=0}^{n_{op}} \eta_{UL}(c_k) \right) \tag{6.2}$$

- The range of downlink cell loads

$$e_1 = w_1 \left(\max_{k=0}^{n_{op}} \eta_{DL}(c_k) - \min_{k=0}^{n_{op}} \eta_{DL}(c_k) \right) \tag{6.3}$$

- A normalised cost based on the number of STP covered,

$$e_2 = w_2 \frac{|T| - \sum_{k=1}^{n_{op}} |c_k|}{|T|} \tag{6.4}$$

- A normalised cost based on the number of mobile stations served,

$$e_3 = w_3 \frac{n_u(M) - \sum_{k=1}^{n_{op}} n_u(c_k)}{n_u(M)} \tag{6.5}$$

- The number of cells with uplink loads above the target cell load plus an allowed margin,

$$e_4 = w_4 \sum_{k=0}^{n_{op}} \begin{cases} \eta_{UL}(c_k) - (d+m) & \text{if } \eta_{UL}(c_k) - (d+m) > 0 \\ 0 & \text{otherwise} \end{cases} \tag{6.6}$$

- The number of cells with downlink loads above the target cell load plus an allowed margin,

$$e_5 = w_5 \sum_{k=0}^{n_{op}} \begin{cases} \eta_{DL}(c_k) - (d+m) & \text{if } \eta_{DL}(c_k) - (d+m) > 0 \\ 0 & \text{otherwise} \end{cases} \tag{6.7}$$

- The number of cells with uplink loads below the target cell load plus an allowed margin,

$$e_6 = w_6 \sum_{k=0}^{n_{op}} \begin{cases} (d-m) - \eta_{UL}(c_k) & \text{if } (d-m) - \eta_{UL}(c_k) > 0 \\ 0 & \text{otherwise} \end{cases} \tag{6.8}$$

- The number of cells with downlink loads below the target cell load plus an allowed margin,

$$e_7 = w_7 \sum_{k=0}^{n_{op}} \begin{cases} (d-m) - \eta_{DL}(c_k) & \text{if } (d-m) - \eta_{UL}(c_k) > 0 \\ 0 & \text{otherwise} \end{cases} \tag{6.9}$$

When this type of cost function is used, a component can be normalised to bring that component's value into a range, normally between 0 to 1. This allows each component to be multiplied by a weight that represents the proportion of influence that component is required to have on the cost function. e_3 provides an example of a component that can be normalised in this way. A suitable denominator for e_3 is the total number of STP in the service area. It is not always possible to find a suitable denominator for use to normalise a given component. Components e_0,

e_1 and e_5 to e_7 are all concerned with network load in either the uplink or the downlink and it is difficult to determine a suitable denominator when trying to normalise, as the maximum network load is not known. Instead, suitable weight values can be specified to control the contribution made by each component to the cost function. In this work components concerning the uplink and the downlink are not normalised, instead each component is multiplied by a weight of 1, which allows the cost function to be naturally weighted, suitably reflecting the operational scenario. The normalised components (*i.e.* e_2 *to* e_3) only become significant for evaluations of solutions in which the load aspects (*i.e.* e_0, e_1 *and* e_5 *to* e_9) have already been improved.

6.1.1 LOCAL SEARCH

Local search is a particulary attractive approach for many combinatorially hard optimisation problems as these problems tend to have a natural neighbourhood structure [71]. Instead of exhaustively searching the entire solution space it can be beneficial to focus on a smaller region or local neighbourhood of a particular solution. A cost function is defined, providing a means of evaluating a solution's performance. This is then used in the local search heuristic with the aim of finding a solution that has a global minimum value. For combinatorially hard problems this requirement is normally relaxed to finding a solution that has a local minimum value and is therefore probably *sub-optimal.*

An initial solution is selected according to some predefined criteria and evaluated using the cost function. A *move* is applied to the current solution to generate a new feasible solution in the neighbourhood and the new solution is evaluated using the cost function. A neighbourhood comprises a number of solutions (neighbours) each one move away from the initial solution. If the new solution is better than any current solution in the neighbourhood then it is exchanged with the best current solution, otherwise it is discarded. The process is repeated until no move improves upon the current solution. This process of moving from one solution to another allows the local search space to be explored.

In general a move is defined as any single change made to the current solution that produces a new and different solution. The process of moving from one network design to another allows the local search space to be explored. In terms of cell planning this translates to a move being any configuration adjustment made to the current network design to produce a new network design. In this optimisation framework a move comprises

- the power setting of an antenna, A_k, can be adjusted by randomly selecting P^{A_k} from the set $\{27, 28, 29, ..., 50\}$ dBm;
- the tilt of an antenna, A_k^{β}, can be adjusted by randomly selecting a value from the set $\{0, -1, -2, ..., -15\}$ where $-15°$ is the maximum available down-tilt;
- for sites with associated directional antennae the azimuths, A_k^{δ}, can be jointly rotated allowing 360 different positions for the same azimuth configuration.

Similar move strategies to those listed above have previously been employed by authors such as Hurley [42] and Kapp-Rawnsley [47] with the main difference being that sites were activated and deactivated during the course of the optimisation. Algorithm 6.1 provides pseudo-code for the local search heuristic in the context of the cell planning problem.

```
Z_old ← Z_init {initial network design}
e_old = e(Z_old) {calculate the cost}
while not finished do
  Generate neighbourhood ζ(Z_old) of Z_old
  Z_new ← Z ∈ ζ : e(Z) = min_{Z∈ζ} e(Z)
  e_new = e(Z_new) {calculate the cost}
  if e_new < e_old then
    Z_old ← Z_new {accept new network design}
    e_old ← e_new
  end if
end while
```

Algorithm 6.1: Pseudo-code for the implementation of local search as used in the optimisation framework to solve various instances of the cell planning problem.

For minimisation problems the traditional forms of local search employ a descent strategy in which the search always progresses in the direction of an improvement resulting from a *downhill* move. The neighbourhood is searched selecting the neighbour that makes the greatest improvement to the cost function until no further improvements can be made and a local optimum has been reached. Another popular approach involves a process of random descent which selects neighbouring solutions randomly and accepts the first solution which makes an improvement to the cost function. The drawback with this technique is that for very long runs of the local search it starts to becomes slower than simple enumeration strategies because of the likelihood of re-sampling previously considered network designs.

Local searches often result in convergence to a local optimum rather than a global optimum. A number of approaches can be taken to attempt to compensate for local search heuristics often arriving and remaining at a local optimum. One approach involves running the local search algorithm a number of times with each run starting from a different initial solution, for example, starting each local search from a differently configured initial network design. Another approach involves making different decisions with regards to the order of the selected moves. In the case where the order of moves is determined randomly from seeds, altering the values of these seeds is likely to result in a different ordering of moves. This in turn is likely to result in a different path being taken through the search space, allowing different network designs to be considered. Alternatively, the size of the neighbourhood could be increased or decreased to widen or reduce the scope of the search.

6.1.2 TABU SEARCH

Meta-heuristic algorithms use problem specific criteria to guide the underlying heuristic towards a good solution, allowing it to escape local optima and search other areas of the search space to find a *global optimum.* One technique for escaping local optima is to allow the heuristic to accept uphill moves or worse moves, albeit sparingly so as not to diverge too far from a suitable solution. As previously discussed in the literature review in Chapter 2 tabu search, which was developed by Glover, Taillard, and de Werra [31], takes a different approach by going beyond the criteria on terminating at a local optimum to allow acceptance of uphill moves. Tabu search has been previously used for optimisation in cell planning and its suitability to the problem formulation approved by Vasquez and Hao [86] (for optimising GSM networks), Amaldi, Capone, and Malucelli [9] (for optimising UMTS networks), Lee and Kang [52] (for CDMA based networks).

Similarly to local search, a cost function is defined and applied to the solution space with the aim of finding a solution that has a minimum value. The idea of exploiting certain forms of flexible memory to control the search process is the principle theme in tabu search. The search space is characterised by a set of *moves* and tabu search maintains a history of the moves encountered during the search. When looking to move from the current solution the best solution is selected providing it is not *tabu restricted*. A tabu move belongs to a history of tabu restricted moves and each move is forbidden for a number of iterations. If there is no improving move available the best non-tabu move (or if all moves are tabu the best tabu move) is accepted. After the accepted move has been made it is added to the history, which is then updated.

The history is normally split into short-term (or recency-based) memory and long-term (or frequency-based) memory. Short-term memory involves preventing the same move being made for a certain amount of time called the *tabu tenure*, whilst long-term memory prevents a move being made if this move accounts for a certain proportion of the moves already made. For example, a move may be tabu if it has been considered in the last n iterations (short-term memory) or has been repeated many times before (long term memory).

Usually *aspiration criteria* are specified that allow a tabu restriction to be overridden if the solution under consideration is the best so far; thus at each iteration a solution is selected from the neighbourhood and if the solution meets the aspiration criteria it is accepted. The conditions for a move to be aspirant are problem specific. In the implementation of tabu search used in this thesis the aspiration criteria specified to always select a move that results in a lower cost network design being produced. Algorithm 6.2 provides pseudo-code for tabu search in the context of the cell planning problem, it should be noted that frequency based memory is not included in this implementation.

6.2 DEFINING THE OPTIMISATION FRAMEWORK

An optimisation framework is presented which enables network designs to be optimised with respect to a number of representative network design scenarios from the KORNET1 data set. The following sections analyse a number of differently weighted versions of the cost function to determine the most suitable formulation of component weights for optimising the networks considered in this work. This in turn allows a number of experiments to be undertaken, using tabu search and local search, with the aim of determining which heuristic produces the most suitably designed network.

$Z_{old} \leftarrow Z_{initial}$ {initial network design}
$e_{old} \leftarrow e(Z_{old})$
$Z_{best} \leftarrow Z_{old}$
$e_{best} \leftarrow e_{old}$
while not finished **do**
  Generate neighbourhood $\zeta(Z_{old})$ of Z_{old}
  $Z_{new} \leftarrow Z \in \zeta : \min_{Z \in \zeta} e(Z)$
  $e_{new} \leftarrow e(Z_{new})$
  if $e_{new} < e_{best}$ **then**
    {Aspiration criteria}
    $Z_{old} \leftarrow Z_{new}$ {accept move}
    $e_{old} \leftarrow e_{new}$
    $Z_{best} \leftarrow Z_{new}$
    $e_{best} \leftarrow e_{new}$ {update best cost}
  else if move applied Z_{old} to produce Z_{new} is not tabu **then**
    $Z_{old} \leftarrow Z_{new}$ {accept move}
    $e_{old} \leftarrow e_{new}$
  else
    $Z_{old} \leftarrow Z \in \zeta : e(Z) = \min_{Z \in \zeta} e(Z)$ {where move is non-tabu or failing that best tabu move}
    $e_{old} \leftarrow e(Z_{old})$
  end if
  update history of moves
end while

Algorithm 6.2: Pseudo-code for the implementation of tabu search as used in the optimisation framework to solve various instances of the cell planning problem

6.2.1 COST FUNCTION ANALYSIS

Experimentation is undertaken for four different sets of component weights, as listed in Table 6.1. Components that have a weight equal to zero are effectively eliminated from the cost function as they have no influence. Non-zero weights are introduced for other components, with the aim of designing networks with high service area coverage, available service for each user and cells with loads that meet a specified target. Table 6.2 provides results for optimisations performed using each version of the cost function, whilst Table 6.3 provides design statistics for the final network. The following observations are made in each case:

	e **version**			
	Simple downlink only	Downlink only	Uplink only	Both links
w_0	0	1	1	1
w_1	0	1	1	1
w_2	1	1	1	1
w_3	1	1	1	1
w_4	0	0	1	1
w_5	1	1	0	1
w_6	0	0	1	1
w_7	1	1	0	1

Table 6.1: Component weights for different versions of the cost function.

Simple downlink only version of the cost function produces cell plans that only improve the average downlink cell load slightly by decreasing from 0.6392 to 0.6318, but the optimisations made are detrimental to the uplink with the average uplink cell load increasing from 0.5551 to 1.7682.

Downlink only version of the cost function introduced non-zero weights for components e_8 and e_9, which are intended to encourage the reduction of the range of cell loads in the cell plan. This is effective producing optimisations, which are more suitable in the uplink than those produced by the simple downlink only version. The uplink average cell load is decreased from 0.5551 to 0.4676 (below target), whilst in the downlink the average cell load decreases slightly from 0.6392 to 0.6320.

Uplink only version of the cost function significantly reduces the uplink average cell load from 0.5551 to 0.3396. The aim in optimisation is for the average cell load to meet the target cell load. If this is not achieved it is better to have the uplink average cell load below the target as opposed to above (as obtained with simple downlink only). The optimisations are suitable in the downlink taking the average cell load from 0.6392 to 0.5648.

	e **version**							
	Simple downlink only		Downlink only		Both links		Uplink only	
e_n	Inital	Optimised	Inital	Optimised	Inital	Optimised	Inital	Optimised
e_0	-	-	-	1.5406	3.0876	1.8321	3.0876	1.6450
e_1	-	-	-	1.4042	4.1369	1.4670	4.1369	0.9651
e_2	0.0	0.0082	0.0	0.0	0.0	0.0	0.0	0.0
e_3	0.0	0.0027	0.0	0.0	0.0	0.0	0.0	0.0
e_4	-	-	-	-	6.4177	1.4000	6.4177	0.5651
e_5	7.1386	2.9916	7.1386	2.8710	7.1386	2.4028	-	-
e_6	-	-	-	-	11.1029	7.3517	11.1029	6.7925
e_7	5.9321	2.2307	5.9321	2.3168	5.9321	2.8622	-	-
e	13.0707	5.2332	20.2952	8.1326	37.8159	17.3157	24.7452	9.9677

Table 6.2: Initial and optimised costs are given for each version of the cost function along with the value of each component e_n

Both links version of the cost function introduces non-zero weights for both uplink and downlink based components with the aim of optimising cell loads in both the uplink and the downlink. In this case downlink improvements are more effective than the downlink only optimisations produced by simple downlink only and downlink only. The uplink optimisations are better than the uplink only optimisations obtained using 'Uplink only' as the average cell is closer to the target load. This version is preferred as it allows the uplink to be optimised (or at least not adversely affected) but also allows the downlink to have the most influence in the cost function.

The results in Chapter 5 provide evidence that downlink is the most limiting link in terms of load for all operational scenarios tested with the network model under consideration. Therefore the optimisation framework is targeted to primarily optimise the capacity in the downlink. *Both links* is the preferred cost function version in this case as it allows the uplink to be optimised (or at least not to be adversely affected) but also allows the downlink to have the most influence in the cost function. It is recommended that version 4 of the cost function is incorporated in the solution framework when optimising the network model, service scenarios and data sets presented in this work. Initial results suggest that optimisations can be made using this version of the cost function for both tabu search and local search.

6.2.2 Selection of heuristic

In order to define an effective framework the most suitable heuristic is selected from either local search or tabu search. Optimisation results generated by the two algorithms are also compared to benchmark results, which are produced by generating a set of randomly configured network designs. The benchmark results have the following attributes:

- each network design is generated by applying a number of moves to the initial network design and can thus be obtained by both local search and tabu search heuristics;
- each network design has the same operational sites as the initial network design.

The optimisations performed using local search and tabu search are expected to produce optimised network designs with costs that are lower than any evaluated network design contained in the set of random network designs. Algorithm 6.3 provides pseudo-code for producing a random set of evaluated network designs.

```
Z_old ← Z_initial
for 1 to number of network designs required do
  Z_new ← Z_old
  for each s_i deployed in Z_new do
    for each A_k at s_i do
      Randomly select a value of P^{A_k}
      Randomly select a value of A_k^β
    end for
    if n_A(s_i) > 1 then
      Randomly rotate azimuths
    end if
    e(Z_new) {evaluate the network design}
  end for
end for
Calculate the maximum, minimum, mean and standard deviation of the collection of network design costs obtained
```

Algorithm 6.3: Pseudo-code to generate a set of random network designs

A number of trials were performed to allow the comparison of results obtained using tabu search, local search and the benchmark tests. The heuristic that produces the best performance across all trials is selected to form the optimisation framework and will be used for optimisation in the remainder of the thesis. The trials included:

- 10 optimisations performed using the simple-downlink-only cost function on the same network for a rural traffic scenario;
- 4 optimisation trials performed using the simple-downlink-only cost function on the same network for a suburban environment;
- 5 optimisation trials performed using the both-links cost function on the same network for a rural environment.

The results of these trials can be summarised as follows:

- Each optimisation generated by tabu search and local search in these trials was compared to relevant benchmark statistics in Table 6.4. In all cases optimisations produced by local search and tabu search were lower than the cost of any network design contained in the benchmark set.

- 70% of the optimisations performed using the simple-downlink-only cost function on the same network for a rural traffic scenario resulted in tabu search producing cost which was between 0.5% and 8% lower than local search. On average tabu search achieved a 70% reduction in cost compared to the 68% reduction achieved by local search. Results are presented in Table 6.5. Optimisations made with local search were on average 54% lower than the minimum benchmark, whilst optimisations using tabu search were on average 58% lower than the minimum benchmark. Downlink and uplink network statistics are presented in Table 6.6 and Table 6.7 respectively.

- 75% of the optimistions performed using the simple-downlink-only cost function for a suburban traffic scenario also resulted in tabu search producing the lowest cost. Results can be seen in Table 6.8. On average tabu search achieved a 54.5% reduction in cost compared to the 52.5% reduction achieved by local search. Optimisations made with local search were on average 49.4% lower than the minimum benchmark, whilst optimisations using tabu search were on average 51.4% lower than the minimum benchmark. Downlink statistics and uplink statistics relating to these optimisations are listed in Table 6.9 and Table 6.10 respectively.

- 60% of the optimisations performed using both-links cost function resulted in tabu search producing the lowest cost. On average tabu search achieved a 74.5% reduction in cost compared to the 73% reduction achieved by local search. Optimisations made with local search were on average 17.5% lower than the minimum benchmark, whilst optimisations using tabu search were on average 18% lower than the minimum benchmark. Results for these optimisations are presented in Table 6.11. Downlink and uplink network statistics are presented in Table 6.12 and 6.13 respectively.

Given this success of tabu search it is incorporated into the cell planning optimisation framework.

		e version			
		Simple Downlink only	Downlink only	**Both links**	Uplink only
	Initial	Opt	Opt	Opt	Opt
DL load					
Network	12.7836	12.6364	12.64	**11.4439**	11.2961
Mean	0.6392	0.6318	0.632	**0.5722**	0.5648
Max	3.0876	1.7209	1.5406	**1.8320**	3.0876
Min	0	0	0	0	0
# Desired	1	4	3	**3**	1
# Over	6	7	9	**8**	10
# Under	13	9	8	**9**	9
STDEV	1.0636	5.4458	0.4058	**0.4412**	0.4002
Total over $m + d$	7.1386	2.9916	2.871	**2.4028**	3.6444
UL load					
Network	11.1029	35.3646	9.3511	**7.3517**	6.7925
Mean	0.5551	1.7682	0.4676	**0.3676**	0.3396
Max	4.1369	24.2130	1.4042	**1.4669**	4.1369
Min	0	0	0	**0**	0
# Desired	0	3	3	**2**	4
# Over	4	5	4	**2**	3
# Under	16	12	13	**16**	13
STDEV	1.0601	5.3196	0.3691	**0.388**	0.3268
Total over $m + d$	7.1386	2.9916	2.871	**2.4028**	3.6444
Coverage					
% STP	100	99.72	100	**100**	100
% MS	100	99.18	100	**100**	100

Table 6.3: Network statistics gathered for optimisations carried out using each version of the cost function

u_d	Version	Iterations	Max e	Min e	Mean e	STDEV
Rur	Simple-downlink-only	3302	156.6393	11.7369	23.2196	48.0785
Sub	Simple-downlink-only	780	361.5230	75.9338	94.9946	159.6673
Rur	Both-links	3467	211.5901	17.4877	33.5718	12.7780

Table 6.4: Benchmark results.

Run	Heuristic	Elapsed seconds	e	e_7	e_5	e_2	e_3
1	Initial		12.328	4.6827	7.6452	0.0	0.0
	LS	16524	4.5066	1.7142	2.7924	0.0	0.0
	TS	14782	**3.5355**	1.6151	1.9198	0.0	0.0006
2	Initial		12.676	1.617	11.0589	0.0	0.0001
	LS	16954	**4.5829**	1.4846	3.0982	0.0	0.0001
	TS	17874	5.2638	2.8234	2.4403	0.0	0.0
3	Initial		13.0707	5.9321	7.1386	0.0	0.0
	LS	17919	**4.1903**	2.11	2.0794	0.0	0.0009
	TS	8573	5.3566	2.7839	2.5727	0.0	0.0001
4	Initial		14.3815	6.4849	7.8965	0.0	0.0
	LS	17978	5.0656	1.9139	3.1517	0.0	0.0
	TS	17639	**4.6717**	2.552	2.0268	0.0653	0.0275
5	Initial		17.3594	4.2562	13.1032	0.0	0.0
	LS	16853	5.0805	2.5393	2.5401	0.0	0.0011
	TS	17457	**4.9704**	2.8273	2.1431	0.0	0.0
6	Initial		18.3015	4.8485	13.453	0.0	0.0
	LS	8148	5.3519	3.2074	2.1445	0.0	0.0
	TS	18031	**4.3857**	1.9347	2.3647	0.0612	0.025
7	Initial		19.9503	6.6016	13.3487	0.0	0.0
	LS	16847	**4.7625**	1.9833	2.774	0.0041	0.001
	TS	18014	4.9764	2.3815	2.5949	0.0	0.0
8	Initial		20.283	5.8944	14.3886	0.0	0.0
	LS	16867	5.5837	2.7332	2.8505	0.0	0.0
	TS	9267	**4.993**	2.4379	2.5547	0.0	0.0004
9	Initial		21.3042	6.3513	14.9529	0.0	0.0
	LS	17857	7.5724	3.8747	3.6976	0.0	0.0
	TS	15253	**5.5868**	1.9711	3.6139	0.0	0.0017
10	Initial		23.0048	5.7883	17.2165	0.0	0.0
	LS	14722	6.7843	3.6662	3.118	0.0	0.0002
	TS	15867	**5.3991**	2.1202	3.2789	0.0	0.0

Table 6.5: Optimisations using simple downlink only cost function carried out within rural traffic scenario.

Run	e	η_{DL}	Network DL	Des	Over	Under	STDEV	Total over $m+d$	% MS	% STP
1	Initial	0.7301	14.6017	1	6	13	0.6188	7.6452	100	
	LS	0.6609	13.2171	3	10	7	0.4403	2.7924	100	100
	TS	0.618	12.3604	7	7	6	0.3692	1.9198	100	99.94
2	Initial	1.0841	21.6819	0	12	8	0.6508	11.0589	100	100
	LS	0.6809	13.6177	3	9	8	1.5575	3.0982	100	100
	TS	0.5879	11.7575	5	8	7	0.4039	2.4403	100	99.94
3	Initial	0.6392	12.7836	1	6	13	1.0636	7.1386	100	99.99
	LS	0.5913	11.8258	5	6	9	6.3645	2.0794	100	99.99
	TS	0.5812	11.624	6	6	8	0.528	2.5727	100	100
4	Initial	1.0153	20.3053	1	7	12	0.9121	13.453	100	100
	LS	0.5414	10.8282	8	4	8	0.4387	2.1445	100	99.91
	TS	0.6276	12.5513	4	8	8	0.3793	2.3647	93.88	99.99
5	Initial	0.6399	12.7979	1	4	15	1.1955	7.8965	100	100
	LS	0.6636	13.2725	5	7	8	0.4631	3.1517	100	100
	TS	0.5642	11.2834	1	8	11	6.3431	2.0268	93.47	97.50
6	Initial	1.0243	20.4869	0	7	13	0.8642	13.1032	100	100
	LS	0.5955	11.9093	6	6	8	34.592	2.5401	100	100
	TS	0.5561	11.1217	4	6	10	0.4704	2.1431	100	97.25
7	Initial	0.9134	18.2671	0	6	14	0.8248	13.3487	100	100
	LS	0.6433	12.8656	6	7	7	0.6137	2.774	99.59	99.90
	TS	0.6117	12.2335	3	9	8	2.5222	2.5949	100	100
8	Initial	0.9947	19.8941	0	5	15	0.8895	14.3886	100	100
	LS	0.6066	12.1329	3	8	9	0.5172	2.8505	100	99.9
	TS	0.6047	12.0941	5	7	8	0.3831	2.5547	100	100
9	Initial	1.0061	20.1216	0	6	14	0.9228	14.9529	100	100
	LS	0.587	11.7397	1	9	10	0.5541	3.6976	100	100
	TS	0.7036	14.0722	4	11	5	1.8717	3.6139	100	99.96
10	Initial	1.1538	23.0757	1	7	12	19.8773	17.2165	100	100
	LS	0.5606	11.2118	0	8	12	0.5124	3.118	100	100
	TS	0.6552	13.105	2	9	9	0.4585	3.2789	100	99.83

Table 6.6: Downlink network statistics relating to optimisations carried out using simple-downlink-only cost function (rural traffic scenario).

Run	Heuristic	η_{UL}	Network UL	Des	Over	Under	STDEV	Total over margin
1	Initial	0.4308	8.6152	1	5	14	0.5373	7.6452
	LS1	0.4290	8.5805	2	3	15	0.3705	2.7924
	TS1	0.4274	8.5474	4	2	14	0.3131	1.9198
2	Initial	0.5566	11.1311	1	9	10	0.3614	11.0589
	LS1	0.8256	16.5121	4	5	11	1.5504	3.0982
	TS1	0.4188	8.3759	3	2	15	0.3647	2.4403
3	Initial	0.5551	11.1029	0	4	16	1.0601	7.1386
	LS1	2.0997	41.9950	4	4	12	6.1734	2.0794
	TS1	0.4426	8.8522	1	4	15	0.5085	2.5727
4	Initial	0.5276	10.5511	0	5	15	0.7626	13.4530
	LS4	0.3905	7.8105	2	3	15	0.4105	2.1445
	TS4	0.4402	8.8038	4	4	12	0.3270	2.3647
5	Initial	0.4624	9.2485	1	3	16	1.1816	7.8965
	LS1	0.4408	8.8158	0	4	16	0.4027	3.1517
	TS1	1.7969	35.9371	2	4	14	6.2158	2.0268
6	Initial	0.4596	9.1918	0	4	16	0.6411	13.1032
	LS1	7.9813	159.6261	3	4	13	33.7518	2.5401
	TS1	0.4312	8.6245	2	2	16	0.4526	2.1431
7	Initial	0.4248	8.4964	1	5	14	0.6550	13.3487
	LS1	0.4709	9.4185	1	3	16	0.5877	2.7740
	TS1	0.9790	19.5807	2	3	15	2.4939	2.5949
8	Initial	0.4457	8.9130	0	4	16	0.6884	14.3886
	LS1	0.4456	8.9121	3	3	14	0.4901	2.8505
	TS1	0.4779	9.5580	2	4	14	0.3604	2.5547
9	Initial	0.4573	9.1468	1	4	15	0.7312	14.9529
	LS1	0.4570	9.1409	2	4	14	0.5378	3.6976
	TS1	0.8827	17.6544	0	7	13	1.8626	3.6139
10	Initial	4.6904	93.8073	0	5	15	19.5433	17.2165
	LS1	0.4252	8.5036	2	4	14	0.4932	3.1180
	TS1	0.4574	9.1488	1	4	15	0.4111	3.2789

Table 6.7: Uplink network statistics for optimisations carried out using simple-downlink-only cost function (rural traffic scenario).

Run	Heuristic	Elapsed seconds	e	e_7	e_5	e_2	e_3
	Initial		87.5779	25.0872	62.4785	0.0057	0.0065
1	LS	21577	40.1415	14.3650	25.7708	0.0024	0.0032
	TS	22363	**38.3094**	14.0443	24.2535	0.0065	0.0050
	Initial		85.4397	21.2293	64.1915	0.0090	0.0099
2	LS	21830	39.0186	15.3144	23.7011	0.0016	0.0015
	TS	22007	**38.9417**	14.0723	24.8684	0.0008	0.0002
	Initial		83.6873	26.7016	56.9822	0.0008	0.0027
3	LS	21824	37.9311	14.6095	23.3200	0.0008	0.0007
	TS	22200	**33.8687**	12.7655	21.0991	0.0033	0.0009
	Initial		69.4384	23.1722	46.2615	0.0024	0.0022
4	**LS**	21833	**36.5886**	14.6207	21.9659	0.0016	0.0004
	TS	22185	36.6327	13.9785	22.6521	0.0016	0.0004

Table 6.8: Optimisations using simple downlink only cost function carried out for a suburban traffic scenario

Run	Heuristic	η_{UL}	Network UL	Des	Over	Under	STDEV	Total over	Total over margin	% Mobiles	% STP
1	Initial	0.6070	61.3085	0	0	5	23	73	1.2579	34.7228	62.4785
	LS	0.5658	57.1426	0	0	7	22	72	0.8581	23.4477	25.7708
	TS	0.8282	83.6528	0	0	6	20	75	3.2400	51.1475	24.2535
2	Initial	0.6845	69.1333	0	0	3	24	74	1.3046	39.7902	64.1915
	LS	0.5050	51.0028	0	0	8	21	72	0.6847	17.2003	23.7011
	TS	0.5519	55.7422	0	0	5	20	76	0.8225	22.7378	24.8684
3	Initial	0.4952	50.0161	0	0	5	23	73	0.7731	23.9393	56.9822
	LS	0.4509	45.5427	0	0	8	14	79	0.5551	12.3590	23.3200
	TS	0.4733	47.8050	0	0	8	16	77	0.5477	13.3457	21.0991
4	Initial	0.4804	48.5193	0	0	10	19	72	0.7002	19.7551	46.2615
	LS	0.4865	49.1408	0	0	8	20	73	0.5810	15.1213	21.9659
	TS	0.4995	50.4465	0	0	8	20	73	0.5835	15.9502	22.6521

Table 6.9: Uplink network statistics relating to optimisations carried out using downlink only cost function (suburban traffic scenario)

Run	Heuristic	η_{DL}	Network DL	Des	Over	Under	STDEV	Total over $d+m$	% Mobiles	% STP
1	Initial	0.9498	95.9300	4	31	66	1.3042	62.4785	99.4286	99.3499
	LS	0.7035	71.0547	19	32	50	0.8692	25.7708	99.7551	99.6777
	TS	0.6916	69.8508	11	37	53	3.2430	24.2535	99.3469	99.4984
2	Initial	1.0159	102.6070	8	39	54	1.3465	64.1915	99.1020	99.0131
	LS	0.6641	67.0779	16	28	57	0.7031	23.7011	99.8367	99.8533
	TS	0.6957	70.2667	14	34	53	0.8351	24.8684	99.9184	99.9783
3	Initial	0.8777	88.6435	2	31	68	0.8634	56.9822	99.9184	99.7338
	LS	0.6722	67.8873	14	32	55	0.5980	23.3200	99.9184	99.9258
	TS	0.6727	67.9460	20	32	49	0.5832	21.0991	99.6735	99.9131
4	Initial	0.8184	82.6619	5	39	57	0.7782	46.2615	99.7551	99.7755
	LS	0.6624	66.9020	17	33	51	0.6073	21.9659	99.8367	99.9602
	TS	0.6755	68.2205	20	32	49	0.6097	22.6521	99.8367	99.9602

Table 6.10: Downlink network statistics relating to optimisations carried out using simple downlink only cost function (suburban traffic scenario).

Run	Elapsed seconds		e	e_2	e_3	e_4	e_5	e_6	e_7	e_0	e_1
1		initial	29.2151	0	0	2.6514	8.0922	6.0739	5.6903	2.2172	4.4901
	17400	LS	12.2368	0	0	0.8687	2.8892	3.7284	2.1852	1.0095	1.5558
	17817	**TS**	**11.3964**	0.0003	0	0.6718	3.0185	2.9224	2.3762	1.0947	1.3125
2		initial	38.8256	0	0	4.1951	9.5423	7.6278	7.1665	3.443	6.851
	17924	**LS**	**13.0252**	0	0	1.3962	2.5242	3.5222	2.6034	1.4581	1.5211
	17825	TS	13.395	0	0	1.4589	2.8011	3.7453	2.4251	1.4581	1.5065
3		initial	81.6357	0	0	31.3938	6.9144	4.9646	3.9661	30.3653	4.0314
	13172	LS	11.4975	0	0	0.6999	2.173	3.504	2.7518	0.9754	1.3935
	17876	**TS**	**10.6406**	0.0001	0	0.6193	3.5705	2.6213	1.4861	1.0163	1.3271
4		initial	81.6357	0	0	31.3938	6.9144	4.9646	3.9661	30.3653	4.0314
	17860	**LS**	**11.0064**	0	0	0.6778	2.504	3.3138	2.0383	1.0137	1.4588
	13172	TS	11.4975	0	0	0.6999	2.173	3.504	2.7518	0.9754	1.3935
5		initial	39.286	0	0	5.1169	7.8965	7.1424	6.4849	5.3299	7.3153
	17439	LS	12.2253	0	0	0.8638	2.6644	3.54	2.628	1.1836	1.3454
	17935	**TS**	**10.4492**	0.0012	0	0.883	2.8149	2.874	1.5093	1.0148	1.352

Table 6.11: Optimisations using both links version of the cost function carried out within a rural traffic scenario.

Run	Heuristic	Mean	Network DL	Max	Min	Des	Over	Under	STDEV	Total $m+d$	% MS	%RTP
1	Initial	0.6991	13.9818	4.4901	0	1	6	13	0.64	8.0922	100.00	100.00
	LS	0.6399	12.7981	1.5558	0	5	8	7	0.373	2.8892	100.00	100.00
	TS	0.649	12.9798	1.3241	0.011668396	3	11	6	0.333	3.0185	100.00	99.97
2	Initial	0.6832	13.6637	6.851	0	1	4	15	0.8841	9.5423	100.00	100.00
	LS	0.5999	11.9989	1.5211	0	4	8	8	0.4052	2.5242	100.00	100.00
	TS	0.6192	12.3833	1.5065	0	6	7	7	0.4203	2.8011	100.00	100.00
3	Initial	0.734	14.679	4.0314	0	2	7	11	6.8215	6.9144	100.00	100.00
	LS	0.5844	11.6881	1.3935	0	2	12	6	0.3377	2.173	100.00	100.00
	TS	0.7245	14.4896	1.3557	0.02863137	2	13	5	0.3552	3.5705	100.00	99.99
4	Initial	0.734	14.679	4.0314	0	2	7	11	6.8215	6.9144	100.00	100.00
	LS	0.6328	12.6566	1.4588	0	5	9	6	0.3487	2.504	100.00	100.00
	TS	0.5844	11.6881	1.3935	0	2	12	6	0.3377	2.173	100.00	100.00
5	Initial	0.6399	12.7979	7.3153	0	1	4	15	1.1955	7.8965	100.00	100.00
	LS	0.6171	12.3413	1.3454	0	4	10	6	0.3693	2.6644	100.00	100.00
	TS	0.681	13.6205	1.3681	0.016132516	5	11	4	0.343	2.8149	100.00	99.88

Table 6.12: Downlink network statistics relating to optimisations carried out using both-links version of the cost function (rural traffic scenario)

Run	Heuristic	Mean	Network UL	Max	Min	Des	Over	Under	STDEV	Total over $m+d$
1	Initial	0.3989	7.9776	2.2172	0	0	5	15	0.5610	8.0922
	LS	0.4267	8.5332	1.0095	0	1	4	15	0.3021	2.8892
	TS	0.4610	9.2202	1.1422	0.0475	6	3	11	0.2714	3.0185
2	initial	0.3864	7.7273	3.4430	0	0	3	17	0.8300	9.5423
	LS	0.4648	9.2968	1.4581	0	6	3	11	0.3808	2.5242
	TS	0.4482	8.9643	1.4581	0	5	2	13	0.3819	2.8011
3	initial	1.8858	37.7159	30.3653	0	2	3	15	6.7183	6.9144
	LS	0.4274	8.5471	0.9754	0	5	3	12	0.2967	2.1730
	TS	0.4799	9.5972	1.0548	0.0385	7	3	10	0.2514	3.5705
4	initial	1.8858	37.7159	30.3653	0	2	3	15	6.7183	6.9144
	LS	0.4375	8.7501	1.0137	0	5	3	12	0.2853	2.5040
	TS	0.4274	8.5471	0.9754	0	5	3	12	0.2967	2.1730
5	initial	0.4624	9.2485	5.3299	0	1	3	16	1.1816	7.8965
	LS	0.4375	8.7495	1.1836	0	4	3	13	0.3200	2.6644
	TS	0.4743	9.4856	1.1323	0.1175	5	4	11	0.2695	2.8149

Table 6.13: Uplink network statistics relating to optimisations carried out using both links cost function (rural traffic scenario)

6.3 TUNING TABU SEARCH

In section 6.2 tabu search was specified as being the most suitable heuristic to be incorporated into the optimisation framework. The following sections look at areas of the optimisation framework that can be customised to improve the results obtained and include:

- determining methods for composing a neighbourhood;
- selecting an effective neighbourhood size;
- selecting a suitable tabu tenure.

Results and analyses produced from these tasks are presented in the following sections. The network scenarios considered at taken from the KORNET1 data set.

6.3.1 NEIGHBOURHOOD COMPOSITION

A neighbourhood is composed of moves that are selected from the population of moves. The process of selection can be made randomly or by using a more strategic method. Experimentation has been undertaken to determine a suitable method for composing neighbourhood structures for use in this optimisation framework. Algorithm 6.4 presents pseudo-code for randomly selecting moves to form a neighbourhood structure. An alternative to randomly constructing a neighbourhood involves targeting antennae that are more likely to significantly reduce the cost function if an improvement is found. This is a deterministic approach that involves targeting over-loaded or under-loaded cells upon which a move can be performed; although only half the antennae are targeted, whilst the other half are still randomly selected. As the network designs produced for the network model and operational scenarios in this work are always downlink limited, the downlink is likely to be the most appropriate link to target. All tests are performed using a tabu tenure of 25% of the number of operational antennae in the network. Algorithm 6.5 provides pseudo-code for generating a *target-load* neighbourhood.

Results illustrated in figures 6.1–6.4 indicate that although the downlink target-load neighbourhood initially produces better optimised solutions (as would be expected) it quickly gets stuck in a local optima, whilst the randomly composed neighbourhood obtains the lowest cost network design by the end of the optimisation. This is likely to be because the downlink-target neighbourhood is more restricted in its exploration of the search space and has a significantly reduced number of random opportunities to make adjustments to other active antennae. For larger problems involving 103 sites, optimisations using the random and the target-load neighbourhood structures shows more similarity to one another. In the optimisation framework it is sufficient to compose a neighbourhood randomly as this composition performs well for small and large problems and is less computationally intensive.

Future developments to the neighbourhood structure should involve introducing more sophisticated moves to ensure the application of the move is effective in reducing the cost function. For example, if one of the cells selected by the target load neighbourhood is over-loaded it is possible that a move will be applied that increases the power of that antenna with the likely result of the cell becoming more loaded. Whereas in this situation it would have been best to decrease the load of the cell by lowering the power setting of that antenna and a more sophisticated strategy would enforce this rule. Thus the basic moves used in this work are likely to have been an impediment to the performance of the target-load neighbourhood.

while list size < neighbourhood size **do**
  {Generate move}
  Randomly select the type of move to be made *i.e.* power, tilt or azimuth
  Given the move type select a value at random within the permitted range
  Perform the move on a randomly selected A_k
  Add the move to the neighbourhood list
  Evaluate the altered network design using the specified cost function
  Record the cost and network statistics
  Reverse the move returning the network design to the original state
end while

Algorithm 6.4: Pseudo-code for generating and evaluating a random neighbourhood

Select $\frac{n}{4}$ most loaded cell from the active set and add associated A_k to a temporary list
Select $\frac{n}{4}$ least loaded cell, c_k, from the active set and add associated A_k to a temporary list
Select $\frac{n}{2}$ A_k at random from the active set and add to a temporary list
$n \leftarrow$ temporary list size
for $i = 1$ to n **do**
  Select the i^{th} A_k in the temporary list
  Randomly select the type of move to be made *i.e.* power, tilt or azimuth
  Given the move type select a value at random within the permitted range
  Perform the move on the selected A_k
  Add the move to the neighbourhood list
  Evaluate the altered network design using the chosen cost function
  Record the cost and network statistics
  Reverse the move, returning the network design to the original state
end for

Algorithm 6.5: Pseudo-code for generating and evaluating a target-load neighbourhood

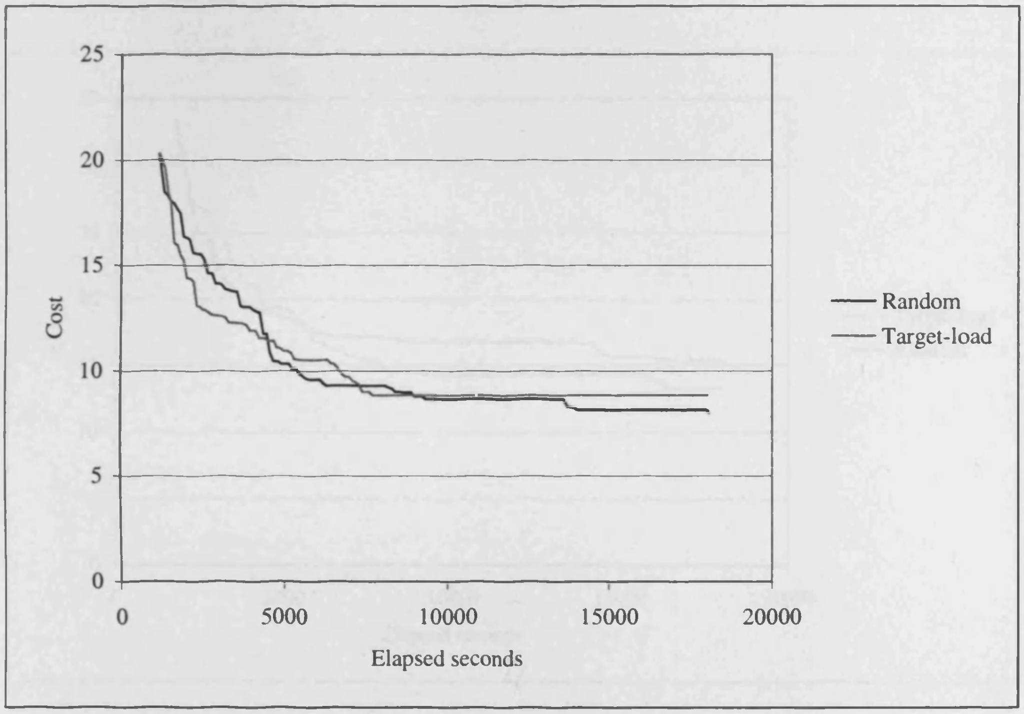


Figure 6.1: A random neighbourhood is compared to a target-load neighbourhood with optimisations preformed using the downlink-only cost function (rural traffic scenario)

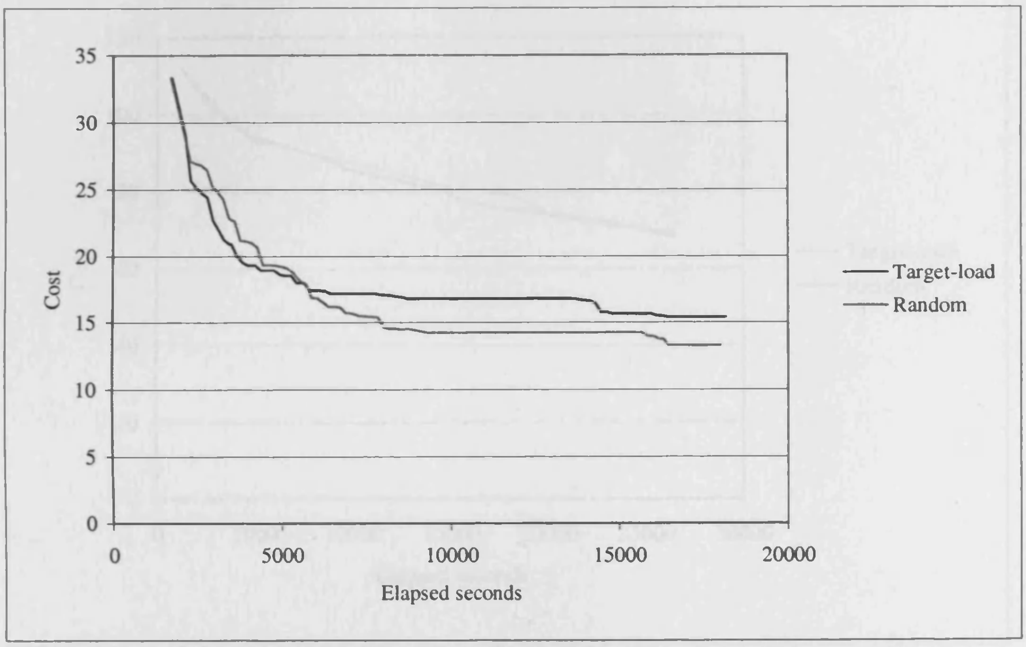


Figure 6.2: A random neighbourhood is compared to a target-load neighbourhood with optimisations preformed using the both-links cost function for a rural traffic scenario

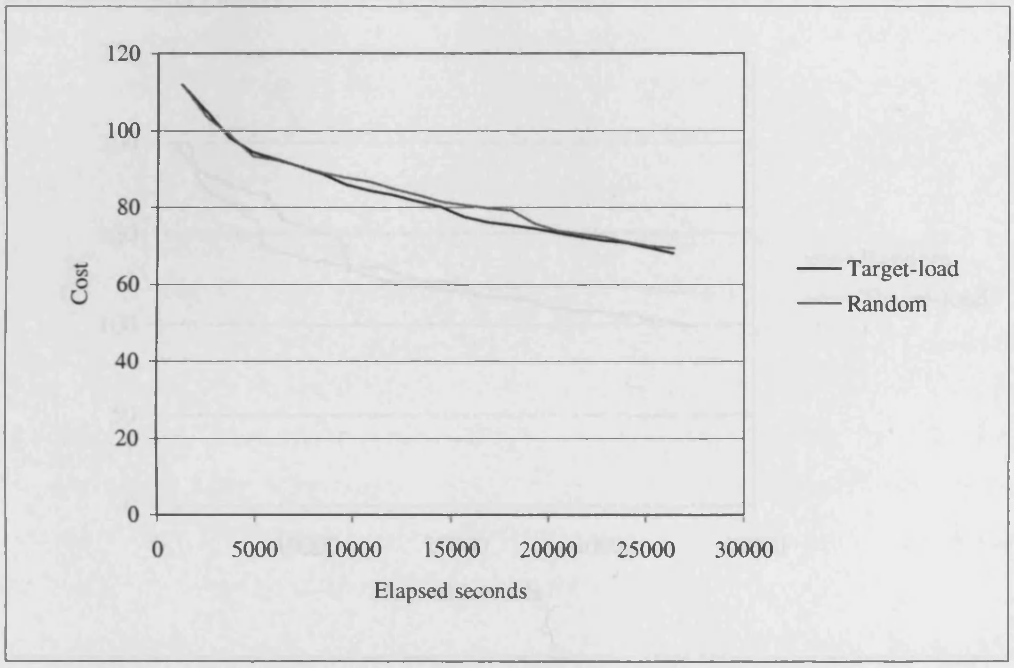


Figure 6.3: A random neighbourhood is compared to a target-load neighbourhood with optimisations preformed using the downlink-only cost function (suburban traffic scenario)

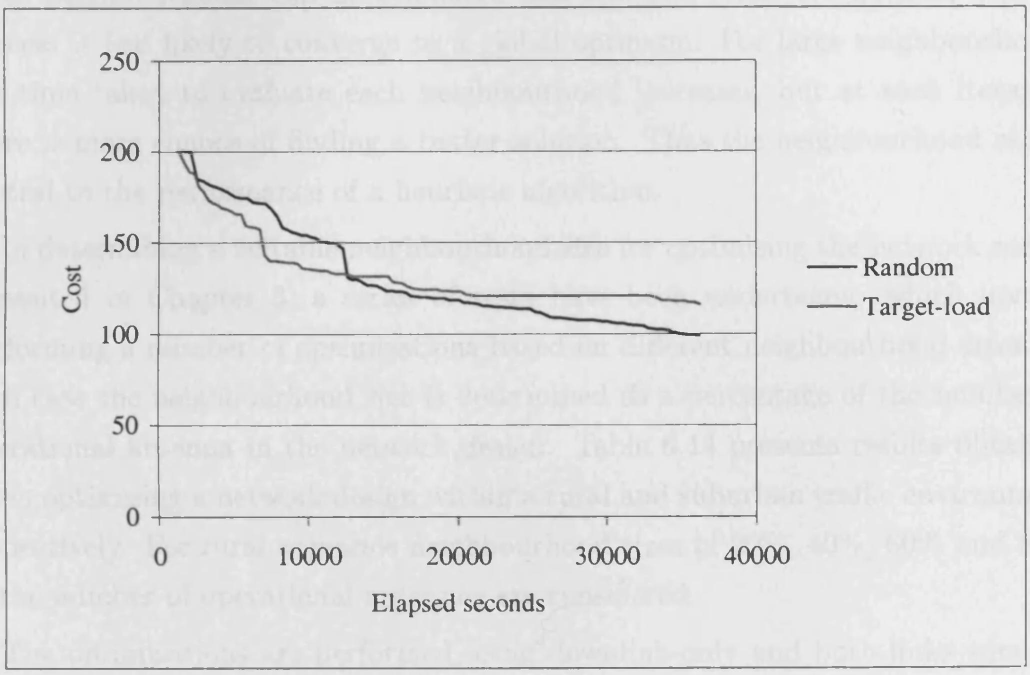


Figure 6.4: A random neighbourhood is compared to a target-load neighbourhood with optimisations preformed using the both-links cost function (suburban traffic scenario)

6.3.2 NEIGHBOURHOOD SIZE

A neighbourhood is typically defined as the immediate area or region surrounding a particular point in the search space and is normally constructed by defining a neighbourhood structure on the search space. In cell planning an example of a neighbourhood could include a selection of operational antenna that are each one move away from the current network design. In determining a suitable neighbourhood size there is a trade-off between solution quality and computation time. Very small neighbourhoods can be evaluated and searched relatively quickly, but the process is less likely to converge to a global optimum. For large neighbourhoods the time taken to evaluate each neighbourhood increases, but at each iteration there is more chance of finding a better solution. Thus the neighbourhood size is central to the performance of a heuristic algorithm.

In determining a suitable neighbourhood size for optimising the network model presented in Chapter 3, a series of tests have been undertaken, which involve performing a number of optimisations based on different neighbourhood sizes. In each case the neighbourhood size is determined as a percentage of the number of operational antenna in the network design. Table 6.14 presents results obtained when optimising a network design within a rural and suburban traffic environment respectively. For rural scenarios neighbourhood sizes of 20%, 40%, 60% and 80% of the number of operational antennae are considered.

The optimisations are performed using downlink-only and both-links versions of the cost function and the following observations are made:

- the most suitable neighourhood size for a rural scenario for the downlink-only cost function is 40% which requires a neighbourhood structure containing eight trial network designs at each optimisation iteration;

- 40% is also suitable for use with both-links version although a neighbourhood specified as 60% of the number of operational antennae produces the best results.

Figure 6.5 and Figure 6.6 provide graphs to illustrate these results by plotting cost against elapsed time and elapsed iterations respectively. These graphs highlight the trade-off between large and small neighbourhoods. For example, when the neighbourhood size is 20% many more iterations are performed in the optimisation period as shown in Figure 6.6, but as the neighbourhood is small the optimisations reside in a local optimum very quickly as shown in Figure 6.5. Larger neighbourhoods produce better optimisation results (for example, see the graph for a neighbourhood size of 80% in Figure 6.5) but are inherently restricted to evaluating less iterations as shown in Figure 6.6.

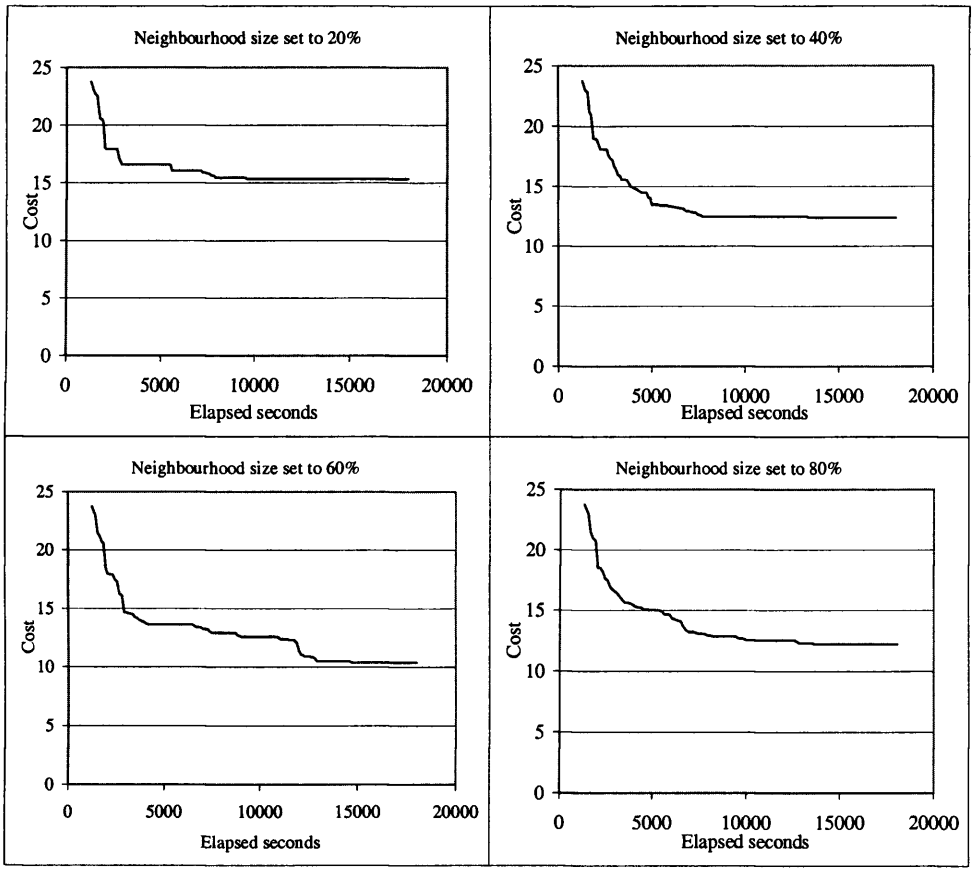


Figure 6.5: Effect of neighbourhood size (cost against time)

The same tests are performed for a suburban traffic scenario which requires a network design with a greater number of operational antennae required to meet the traffic demand. Firstly optimisations are undertaken for the downlink-only cost function considering neighbourhood sizes of 20%, 40%, 60% and 80%. All tests are performed using a tabu tenure of 25% of the number of operational antennae in the network. As this network design has more antennae than are required in rural scenarios an extra round of tests are undertaken to refine the selection of

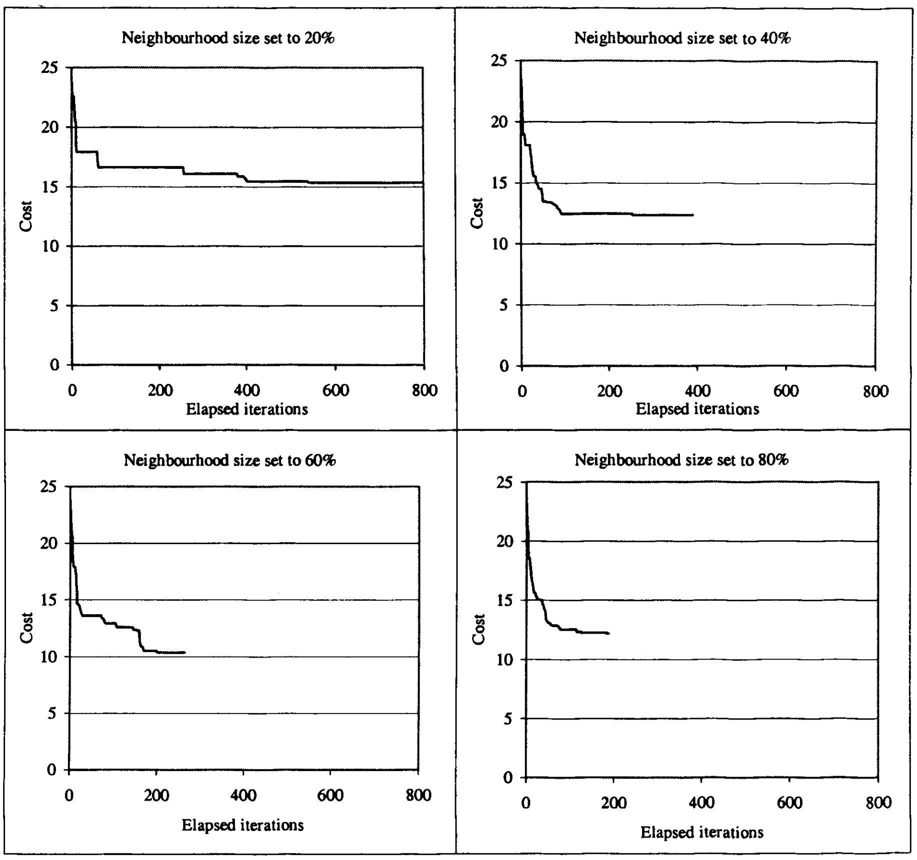


Figure 6.6: Effect of neighbourhood size (cost against iteration)

neighbourhood size considering neighbourhood sizes of 10%, 15%, 25% and 35%. Results for all neighbourhood size tests are listed in Table 6.14.

The results of these tests enable conclusions to be drawn as to how the neighbourhood size will be specified in the reminder of the thesis. When considering a rural scenario the neighbourhood size should be determined by taking 60% of the number operational antennae in the network design. For suburban scenarios results indicate that smaller neighbourhoods are more appropriate for reasonable optimisation run times and in these cases a neighbourhood size which is 10% of the number of operational antennae should be applied. In the cases considered for neighbourhood size

- 40% or 60% of the number of operational antennae in the rural scenario the number of operational antennae is 12;

- 10% of the number of operational antennae in the suburban scenario the number of operational antennae is 10.

This gives neighbourhoods with between 10 and 12 candidate network designs in suburban and rural scenarios. It is likely that a reduced percentage would be better for an urban scenario, but in this work 10% is assumed.

e version	u_d	n_{op} %	Initial	Optimised
Simple downlink only	Rural	20	10.8805	5.6816
		40	**10.8805**	**3.6642**
		60	10.8805	3.9909
		80	10.8805	3.6681
Downlink Only	Rural	20	20.2952	9.3409
		40	**20.2952**	**7.9963**
		60	20.2952	8.5296
		80	20.2952	8.4989
Downlink only	Suburban	5	111.8740	66.1809
		10	**111.8740**	**65.9781**
		15	111.8740	66.3520
		20	111.8740	68.7051
		35	111.8740	79.1096
		40	111.8740	79.1096
		60	111.8740	82.1714
		80	111.8740	82.7125
Both links	Rural	20	23.7435	15.3453
		40	23.7435	12.3981
		60	**23.7435**	**10.3878**
		80	23.7435	12.1911
Both links	Suburban	5	151.365	97.8869
		10	**151.365**	**92.5651**
		15	151.365	92.7334
		20	151.365	96.3586

Table 6.14: Neighbourhood size test results

6.3.3 TABU TENURE

The more sophisticated the heuristic the more tuning and judgement are required in tailoring it to the problem. As discussed in Section 6.1.2, the idea of exploiting certain forms of flexible memory to control the search process is the principal theme in tabu search. The introduction of a memory feature involves a number of extra parameters and tuning decisions that make tabu search a more complex heuristic to implement than local search.

When a move is applied to alter one attribute of a single antenna, it is subsequently added to the memory and becomes a *tabu move*, this prevents any further move being applied to that antenna for the course of the tabu move's tenure. Glover [30] states that an important aspect of a tabu search using recency based memory is to determine a 'good' value for the tabu tenure. This assertion was later supported by Lee and Kang [52] who applied tabu search to the cell planning problem. When deciding on a suitable tabu tenure Glover [30] suggests taking either a static approach, which involves stating the tenure as some constant relating to the environment, or a dynamic tuning approach, which allows the tenure to vary randomly or systematically between an upper and a lower bound. This work applies static tabu tuning but both approaches are discussed in some detail in [31]. With regards to a static approach to tuning Glover [30] states that experimentation should be undertaken to determine a suitable value for the problem in question as preferred tabu tenure values are largely problem specific. In Glover's experience, tenures of between 7 and 20 iterations appear to work well for a variety of problem cases.

Pseudo-code for the static technique used in this work to determine a suitable recency tenure is provided in algorithm 6.6. This technique involves setting the tenure as a percentage of the total number of operational antennae in the network allowing the tenure to be a constant associated with the environment. More detailed tabu tenure tests can be undertaken if required, determined by granularity of percentages considered.

Tabu tenure tests have been undertaken for optimisations using a number of different versions of the cost function and results are presented in Table 6.15. A tabu tenure of 25% of the number of operational antennae appears to be the most effective in most of the scenarios considered, in particular when using the downlink

```
Specify a starting percentage of n_op
Specify a final percentage of n_op
Specify an increment
while percentage ≤ final percentage do
   tabu tenure ← percentage
   Perform tabu search optimisation
   Record the cost of the best network design
   Increment percentage
end while
Select the tabu tenure that best minimises the cost function
```

Algorithm 6.6: This algorithm can be used to assist in statically determining a suitable tabu tenure for use with recency memory

only cost function as stated in Table 6.1.

If the process for generating a neighbourhood structure is altered from random selection to a more targeted method which favors cells with high or low cell loading as opposed to randomly selecting the antennae, results indicate that a tabu tenure of 25% can be applied effectively and is not affected by alterations to the composition of the neighbourhood.

From the tabu tenure results it is recommended that a tabu tenure of 25% should be used with the downlink only cost function. It is important that time is spent in finding an effective tabu tenure, but for a pragmatic approach to network design this testing should not escalate to exhaustive experimentation. Glover [30] clearly states that it is a 'good' tenure that is required not the 'best' tenure. The methods presented allow a 'good' tabu tenure to be determined quickly.

One aspiration criterion is included in this implementation of tabu search. The aspiration criterion in question is often applied in the literature [9, 86] and states that a tabu status of a trial move can be overridden if it yields a solution better than anything obtained to that point in the optimisation.

6.3.4 Initial network design

Figure 6.7 illustrates a selection of tabu search optimisations taken from the trials discussed in Section 6.2. By comparing the initial and optimised costs illustrated

e version	u_d	Neighbourhood	e	Tabu tenure as a percentage of operational antennae				
				0 %	25%	50%	75%	100%
Simple downlink only	Rural	Random	Initial	13.0707	13.0707	13.0707	13.0707	13.0707
			Optimised	7.8543	5.4496	**5.1869**	6.7684	5.6945
Simple downlink only	Rural	Target-load	Initial	13.0707	13.0707	13.0707	13.0707	13.0707
			Optimised	6.3901	**5.5651**	7.3261	7.3261	7.6817
Downlink only	Rural	Random	Initial	20.2952	20.2952	20.2952	20.2952	20.2952
			Optimised	9.3421	**8.6620**	9.7222	11.7350	9.7018
Downlink only	Rural	Target-load	Initial	20.2952	20.2952	20.2952	20.2952	20.2952
			Optimised	11.6182	**10.3127**	11.6745	12.3985	12.3985
Downlink only	Suburban	Random	Initial	111.8740	111.8740	111.8740	111.8740	111.8740
			Optimised	59.5027	**59.0574**	59.3549	59.3549	59.5027
Both links	Rural	Random	initial	33.3078	33.3078	33.3078	33.3078	33.3078
			Optimised	14.2618	**12.7440**	14.3025	14.5610	15.0969
Both links	Suburban	Random	Initial	168.5694	168.5694	168.5694	168.5694	168.5694
			Optimised	75.8383	**73.2517**	76.9646	77.8423	77.8423

Table 6.15: Tabu tenure results

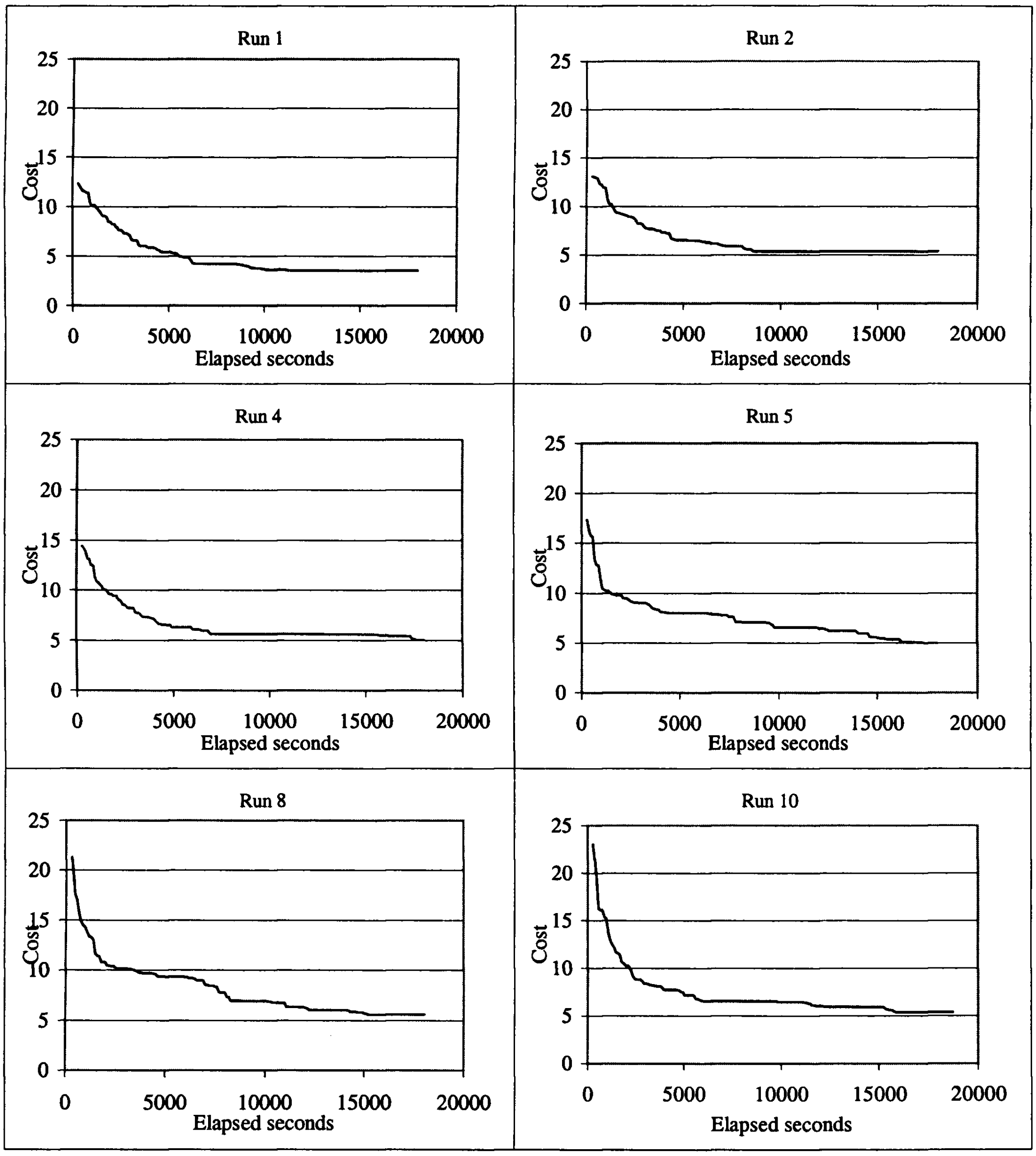


Figure 6.7: Multiple tabu search starts

in each of the graphs in Figure 6.7 the following observation is made:

- optimisations that start from a lower cost are likely to produce the best optimised costs at the end of the optimisation period, indicating that the initial network configuration affects the quality of the solutions obtained.

It is likely that improving the initial network design will result in more effective optimisations being found. Motivated by this observation, a set of random network designs can be easily generated at the start of each optimisation by utilising algorithm 6.3. The network design that best minimises the cost function is selected from the set to become the network design from which optimisation will commence.

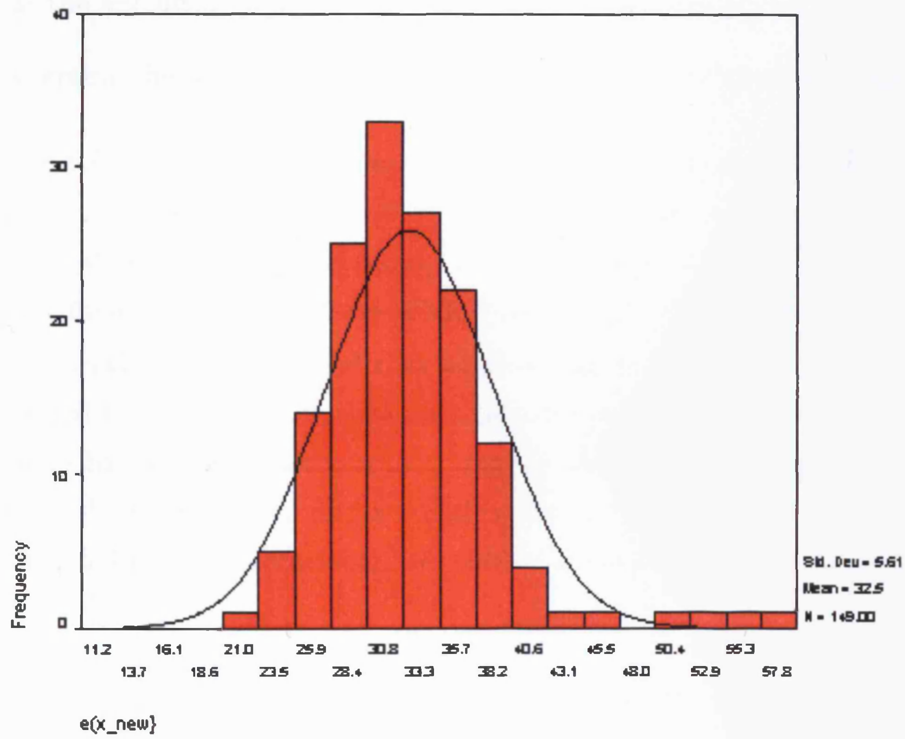


Figure 6.8: Benchmark of costs are almost normally distributed

Clearly, there is a trade-off between time spent in finding a good initial network design and time spent optimising with the framework. The graph in Figure 6.8 illustrates the distribution of random network design costs against their frequencies.

From this graph it can be seen that the cost is almost normally distributed with a mean of 32. From these results it can be assumed that the probability of picking a network design with a cost that is less than or equal to the 32 is approximately $\frac{1}{2}$. Therefore the probability of generating a network design with a fairly low cost within 10 attempts is $\frac{1}{2}^{10} = 0.93$. Thus, it is likely that a reasonable initial network design can be found within the first 10 randomly generated network designs. The application of this is checked by performing optimisations from three different starting network designs generated by

(a) selecting one network design at random from the set of benchmark network designs;

(b) applying the network design used at the network dimensioning stage (defined as the *default* network design with all $P_k^A = 40$ and $A_k^\beta = 0$);

(c) selecting the best network design from ten random network designs.

Figure 6.9 presents results from these tests. The results show that randomly selecting a network design does not produce the best initial cost, but this result is intuitive and expected. Optimisations commencing from a default network design perform similarly to those commencing from the benchmark network design.

It was previously determined that approximately ten random network designs are required to find a suitably low cost network design. From this result it seems reasonable to use the neighbourhood size to determine the number of random network designs required to find a suitably low cost network design. For example, in Section 6.3.2 it was recommended that the following neighbourhood sizes be used:

- 60% of the number of operational antennae in the rural scenario amounted to a neighbourhood size of 12;
- 10% of the number of operational antennae in the suburban scenario amounted to a neighbourhood size of 10.

As these neighbourhood sizes are greater or equal to ten, it seems reasonable to use the neighbourhood size to determine the number of random network designs to consider. This has the added advantage of being scalable when optimising

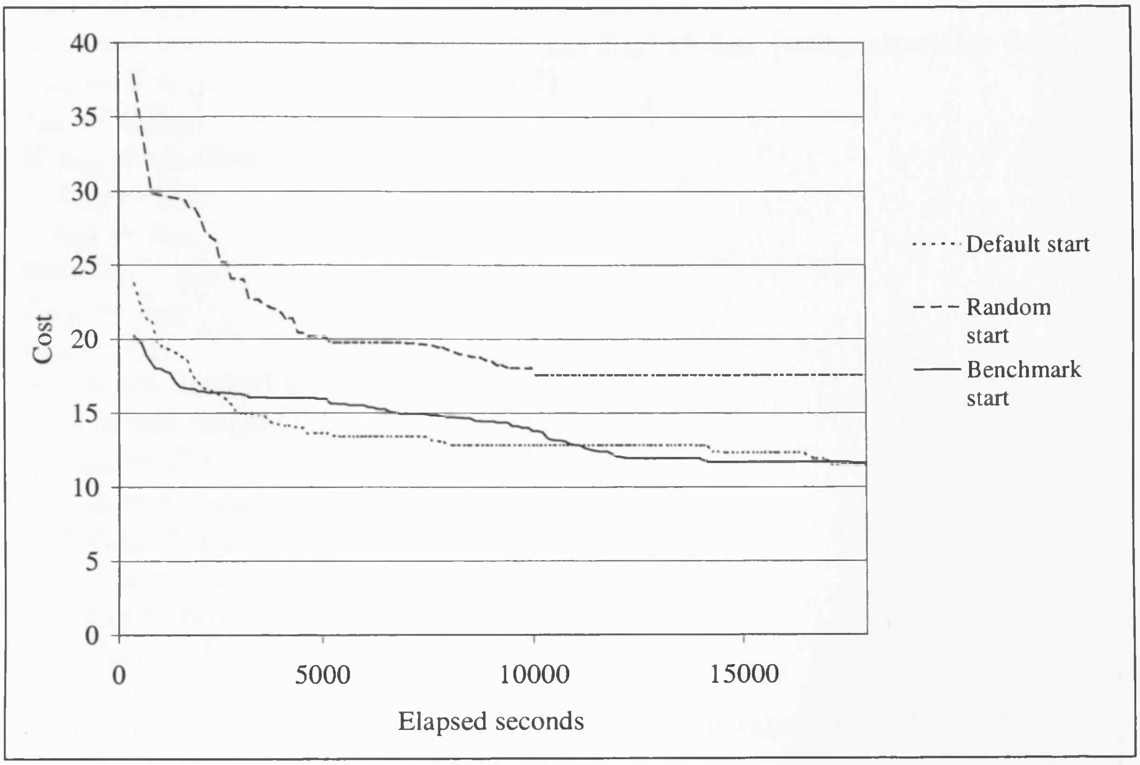


Figure 6.9: Default, random and benchmark

different size networks. Algorithm 6.7 provides pseudo-code for tabu search when starting from the lowest cost random network design. This implementation is applied subsequently in the optimisation framework.

6.4 SUMMARY

The optimisation framework has been customised for use with the network model. The effect of neighbourhood size and neighbourhood composition has been considered for a variety of optimisations using a number of different versions of the cost function. Results and methods have been provided that allow the effective selection of a suitable tabu tenure for recency memory. All optimisations performed using local search and tabu search produce better results than those found by randomly sampling the solution space. Previous authors state the performance of local search is highly dependent on the starting solution and this is consistent

$Z_{old} \leftarrow Z_{init}$ {initial network design}
$e_{old} = e(Z_{old})$
Generate benchmark neighbourhood $\zeta_{bm}(Z_{old})$ of Z_{old} {using algorithm 6.3}
$Z_{bm} \leftarrow Z \in \zeta_{bm} : e(Z) = \min_{Z\in\zeta_{bm}} e(Z)$
$e_{bm} \leftarrow e(Z_{bm})$
if $e_{bm} < e_{old}$ **then**
  $Z_{old} \leftarrow Z_{bm}$
  $e_{old} \leftarrow e_{bm}$
end if
$Z_{best} \leftarrow Z_{old}$
$e_{best} \leftarrow e_{old}$
while not finished **do**
  Generate neighbourhood $\zeta(Z_{old})$ of Z_{old}
  $Z_{new} \leftarrow Z \in \zeta : e(Z) = \min_{Z\in\zeta} e(Z)$
  $e_{new} \leftarrow e(Z_{new})$
  if $e_{new} < e_{best}$ **then**
    $Z_{old} \leftarrow Z_{new}$ {accept move}
    $e_{old} \leftarrow e_{new}$
    $Z_{best} \leftarrow Z_{new}$
    $e_{best} \leftarrow e_{new}$ {update best cost}
  else if move applied Z_{old} to produce Z_{new} is not tabu **then**
    $Z_{old} \leftarrow Z_{new}$ {accept move}
    $e_{old} \leftarrow e_{new}$
  else
    $Z_{old} \leftarrow Z \in \zeta : e(Z) = \min_{Z\in\zeta} e(Z)$ {where move is non-tabu or failing that best tabu move}
    $e_{old} \leftarrow e(Z_{old})$
  end if
  update history of moves
end while

Algorithm 6.7: Pseudo-code for the implementation of tabu search used in the optimisation framework to solve various instances of the cell planning problem

with the results presented for both local search and also tabu search. Although tabu search needs to be tuned effectively to find a suitable recency tenure, it remains a highly suitable and robust algorithm for cell planning. In the majority of optimisation comparisons between tabu search and local search, tabu search produced the best solution and is the chosen heuristic for the optimisation framework. In general, better initial network designs produce better final solutions and this can be achieved by randomly generating a set of network designs, evaluating each one and selecting the network design that best minimises the cost function. This approach is incorporated into the optimsiation framework.

For the remainder of the thesis the optimisation framework will be customised with the following:

- neighbourhoods that are composed of randomly selected moves;
- rural scenarios will have a neighbourhood size of 60% of the number of operational antennae;
- suburban and urban scenarios will have a neighbourhood size of 10% of the number of operational antennae;
- a tabu tenure equal to 25% of the number of operational antennae;
- aspiration criteria of always accepting a move if it is the best move so far;
- use of both links cost function.

CHAPTER 7

NETWORK OPTIMISATION

Adopting a practical approach to network design, this chapter considers if there is an advantage in using the proposed network dimensioning techniques presented in Chapter 4 and Chapter 5 as a precursor to optimisation. In the situation where a network planner has a limited amount of time to optimise a network this chapter assesses whether the application of effective site selection techniques to produce an initial network design provides an advantage at the optimisation stage. After a fixed time optimising it is possible to determine if the network designs formed from less effective site selections can significantly improve during optimisation and possibly surpass any initial advantage in making more sophisticated site selections. In the absence of a static-system level simulator to validate the suitability of the optimised network designs, the method for estimating the number of sites in Chapter 4 is used to provide a means of validating and comparing the progress made by the optimisation framework. Consideration is also given to the effects of basing the optimisation cost function on multiple snapshot evaluation as opposed to a single snapshot cost function. This determines if a more complex cost function (that may require more time to evaluate) will produce better optimisation results than a single snapshot cost function in a fixed time period.

7.1 NETWORK EVALUATION

During optimisation a cost function is defined that allows the current network design to be evaluated at each iteration. The cost function is normally composed from a combination of metrics gathered from the evaluation of the network design for a particular snapshot of traffic as discussed in Chapter 6. This approach allows the time taken in evaluating the cost function to be reduced and is referred to as a *single snapshot cost function* in this work.

An approach to network evaluation not yet considered in the literature, involves defining a cost function composed of metrics gathered from a network design that is evaluated for multiple traffic snapshots. This approach is referred to as a *multiple snapshot cost function* in this work and is based on *Monte-Carlo* sampling used in static system-level simulators* [22, 49]. A multiple snapshot cost function is evaluated by accruing the cost of each evaluated single snapshot cost function. Multiple snapshot evaluation presents a trade-off between the evaluation time and the level of confidence in network quality. Computational time for a network to be evaluated many times is large, but confidence in the network design being robust increases with each successful snapshot evaluation.

Alternatively, evaluating a network design for one shared-load traffic snapshot may provide a compromise between single and multiple snapshot evaluation and provides a more linear relationship between capacity and coverage, which may be an advantage in optimisation. This approach is referred to as *shared snapshot cost function.* When using a shared snapshot cost function and considering non-uniformly distributed traffic, shared-load distribution can be adapted to characterise the service area in terms of two different densities *i.e.*, the density of users in the cluster and the density of users in the service area as shown in Figure 7.1. The traffic is therefore characterised as follows:

- Each STP in the approximate area of the cluster is given an uplink bit-rate and downlink bit-rate calculated by sharing the total uplink bit-rate and downlink bit-rate of mobile station users distributed within in the cluster in snapshot 1 (labelled u_d(cluster) in Figure 7.1);

- Each STP in the remainder of the service area is given an uplink bit-rate and downlink bit-rate calculated by sharing the total uplink bit-rate and downlink bit-rate of mobile station users distributed outside the cluster in snapshot 1 (labelled u_d(remaining) in Figure 7.1).

*A static system-level simulator uses Monte-Carlo statistical sampling to allow multiple evaluations of the same network design to be performed with respect to a set of traffic snapshots.

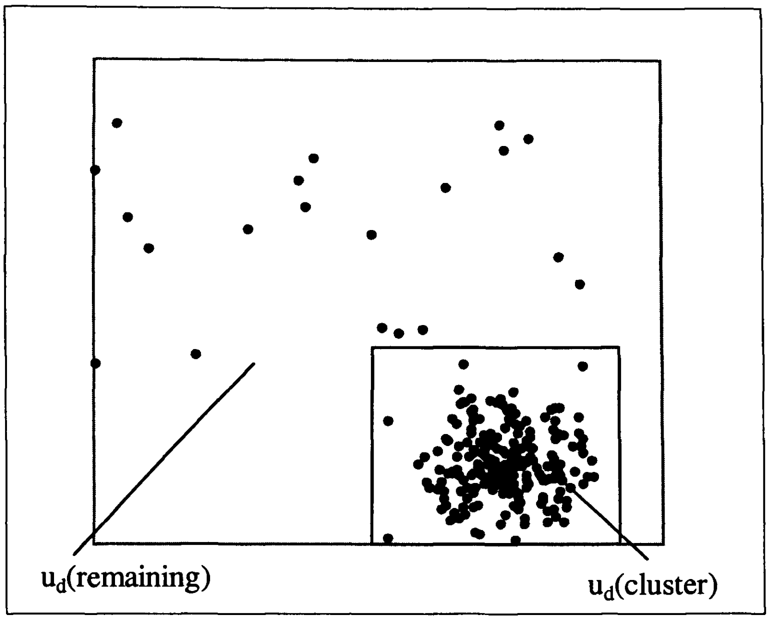


Figure 7.1: Two different densities

Two sets of optimisations are performed on the same network. One set involves network evaluations for a uniform traffic scenario and the other set involves network evaluations for a non-uniform traffic scenario. Each set consists of three optimisations and includes

- a single snapshot cost function (based on snapshot 1, as illustrated in Figure 7.2 and Figure 7.3);
- multiple snapshot cost function (based on snapshot 1, snapshot 2 and snapshot 3, as illustrated in Figure 7.2 and 7.3);
- shared snapshot cost function (based on a shared-load snapshot as defined in Chapter 3 for uniformly distributed traffic and as above for non-uniformly distributed traffic).

Optimisations are performed for five hours and during this time each evaluation procedure may perform a different number of iterations. The best network design found in each optimisation is evaluated using a single snapshot cost function for snapshot 1, snapshot 2 and snapshot 3. This enables the results from each optimisation to be compared as shown in Table 7.1 and Table 7.2.

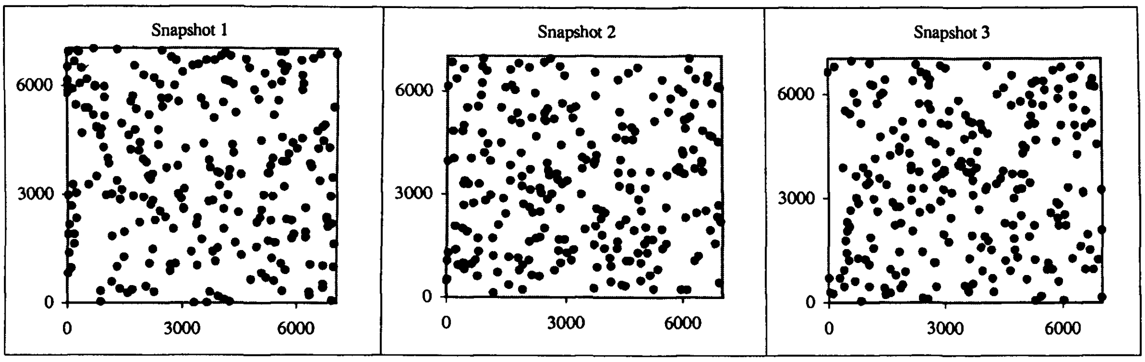


Figure 7.2: Three snapshots with uniformly distributed traffic

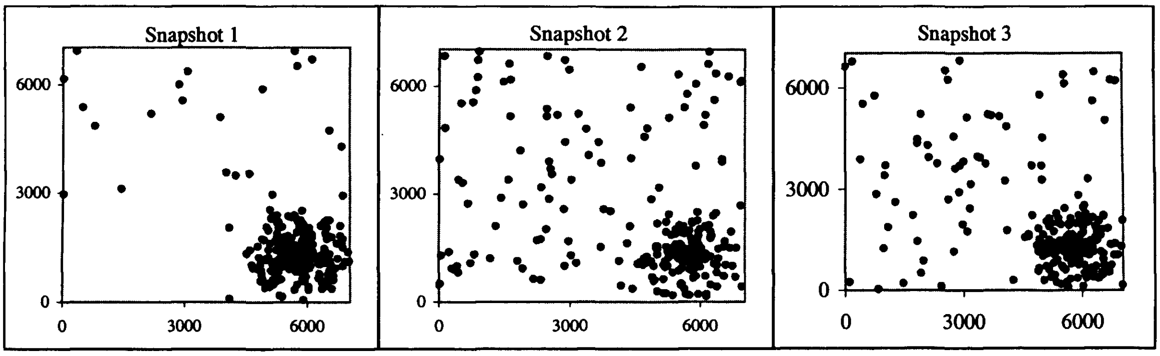


Figure 7.3: Three snapshots with non-uniformly distributed traffic

The following observations are made for snapshot 1:

- when considering uniformly distributed traffic the best network design cost for evaluating snapshot 1 is found using a shared snapshot cost function with the second best network design being found using a single snapshot cost function. During this period 200 iterations are performed using the shared snapshot cost function compared to 284 iterations using the single snapshot cost function.

- when considering non-uniformly distributed traffic a single snapshot cost function produces a better optimised cost than a shared snapshot cost function. Single snapshot cost function produces the lowest average cost and smallkest cost range after 187 iterations, whilst a higher cost is obtained at the same number of iterations with a shared snapshot cost function.

	Single	Multiple	Shared
Snapshot 1	15.1696	18.5227	14.057
Snapshot 2	16.83	16.4780	18.657
Snapshot 3	20.1905	14.9801	14.2578
Sum of 3 snapshots	53.9333	49.9809	46.9727
Mean of 3 snapshots	17.3967	16.6603	15.6573
STDEV of 3 snapshots	2.0886	1.4520	2.1227
Sum across 20 snapshots	363.0287	365.1471	354.8983
Mean of 20 snapshots	18.1511	18.0676	17.7448
STDEV of 20 snapshots	1.8695	1.3590	5.7539

Table 7.1: Network evaluation for uniformly distributed traffic scenarios

	Single	Multiple	Shared
Snapshot 1	35.941	37.9413	39.9828
Snapshot 2	30.1989	27.702	55.6053
Snapshot 3	33.8726	30.0572	33.5056
Sum of 3 snapshots	100.0125	95.7005	129.0938
Mean of 3 snapshots	33.3375	31.9002	43.0312
STDEV of 3 snapshots	2.3745	4.3786	11.3608
Sum for 20 snapshots	683.9674	666.2222	738.6828
Mean of 20 snapshots	34.1983	33.3114	36.9341
STDEV of 20 snapshots	3.1792	4.1807	6.2476

Table 7.2: Network evaluation for non-uniformly distributed traffic scenarios

Therefore if optimisations are required for one snapshot only it is recommended that a single snapshot cost function is used and this result is intuitive and expected. In order to increase confidence in the network being robust it may be desirable to evaluate the network for a number of different snapshots. The following results are produced when assessing the quality of the network for snapshot 1, snapshot 2 and snapshot 3:

- a multiple snapshot cost function achieves a similar cost as the single snapshot cost function after the same number of iterations, but obviously takes approximately three times as long to reach that point. For example, the single snapshot cost function achieves a cost of 18.0842 for snapshot 1 after 52 iterations, whilst the multiple snapshot cost function (for three snapshots) achieves the slightly higher cost of 18.5227 for snapshot 1 after 52 iterations;

- A shared snapshot cost function is the most effective in optimising the network across three uniformly distributed snapshots producing the lowest average cost;

- A multiple snapshot cost function is the most effective in optimising the network across three non-uniformly distributed snapshots.

Using a multiple snapshot cost function in non-uniform traffic scenarios produces a network design that is more robust as a result of being optimised with respect to more than one snapshot. This is reflected when the optimised network design is evaluated over twenty other snapshots. The network design produced from the multiple snapshot cost function produces an accrued cost over twenty snapshots of 666.2222, which is lower than the cost of a network design produced from a single snapshot cost function (683.9674) or shared snapshot cost function (738.6828) when evaluated over the same twenty snapshots. In summary the following conclusions can be drawn:

- a single snapshot cost function is best when only needing to evaluate one snapshot and this result is intuitive and expected;

- a multiple snapshot cost function is highly suitable when evaluating non-uniform traffic scenarios and requiring more than one snapshot evaluation to increase confidence in the network's ability to cope with different traffic scenarios;

- a shared snapshot cost function is suitable if the traffic in the service area can be easily characterised using shared-load distribution. This was especially evident when evaluating uniformly distributed traffic scenarios. When using shared snapshot cost function for non-uniformly distributed users the results, although competitive, were not as effective as a single or multiple snapshot cost function.

7.2 SITE SELECTION

The experiments presented in the following three sections consider whether making effective site selections from the set of candidate sites prior to optimisation produces better evaluated network designs at the start and end of optimisation. This idea is investigated by comparing a number of evaluated network designs (the sites for which were selected using the algorithms presented in Chapter 5) before and after network configuration optimisation is performed using the framework; consideration is given to whether the algorithms that are deemed to be the most effective at the site selection optimisation stage of the cell planning process provide an advantage in optimisation. More specifically the following experiments are undertaken:

- **Uniformly distributed traffic:** this experiment considers a number of KORNET1 network designs required to meet mixed voice and multimedia service demand in rural, suburban and urban traffic environments for uniformly distributed mobile station users;
- **Non-uniformly distributed traffic:** this experiment considers a number of KORNET1 network designs required to meet mixed voice and multimedia service demand in rural, suburban and urban traffic environments for non-uniformly distributed mobile station users;
- **Real network data set:** this experiment determines if the application of both the site selection optimisation techniques and the optimisation framework can be successfully applied to networks produced from a real world data set.

7.2.1 UNIFORMLY DISTRIBUTED TRAFFIC

When considering uniformly distributed traffic, site selections made using pattern-approximation, service-potential-random and service-potential-deterministic algorithms produced initial network designs with a lower average cell load than site selections made randomly. This experiment is aimed at determining if the advantages made in using sophisticated site selection algorithms are still evident at the end of network configuration optimisation. This experiment is carried out for six different KORNET1 network design scenarios and includes:

(a) A network design requiring 20 sites, each with a single omnidirectional antenna, required to meet the traffic demand in a rural scenario;

(b) A network design requiring 104 sites, each with a single omnidirectional antenna, required to meet the traffic demand in a suburban scenario;

(c) A network design requiring 216 sites each, each with a single omnidirectional antenna, required to meet the traffic demand in a urban scenario;

(d) A network design requiring 7 sectorised sites for a rural traffic scenario;

(e) A network design requiring 34 sectorised sites for a suburban traffic scenario;

(f) A network design requiring 61 sectorised sites for a urban traffic scenario;

Each of the above network design scenarios are required to meet the traffic demands of uniformly distributed mobile station users requiring a mix of voice and multimedia services. Results from a number of these scenarios are discussed specifically in the following paragraphs; the remainder of the results are presented in appendix D.

The two graphs displayed in Figure 7.4 collectively illustrate the performance of a network design before and after optimisation is performed. The first graph, entitled 'Site selections', illustrates the average downlink cell load of four independent network designs. These network designs were presented in Chapter 5, having been generated from application of the site selection algorithms. The second graph, entitled 'Optimisations', displays the cost obtained when each of the network designs is optimised.

By comparing the graphs in Figure 7.4 it can be seen that the network designs produced from site selections made by applying the pattern-approximation, service-potential-deterministic and service-potential-random algorithms have lower initial costs than the network design produced from random site selections. The pattern-approximation algorithm was noted as producing the most effective site selections prior to optimisation and also produces the lowest initial cost, as shown in Table 7.3. However, by the end of the optimisation period service-potential-deterministic, having started optimisation with a worse cost network design, produces the lowest cost network.

The improvements made to the average uplink and downlink cell load after optimisation can be compared to the average uplink and downlink cell loads of the nominal network design produced from site selection. Figure 7.5 presents a graph displaying the average downlink and uplink cell load of each dimensioned network design. In each case the average downlink cell load obtained after optimisation is lower than the average downlink cell load obtained prior to optimisation. This process of comparing back to the average cell load obtained before optimisation is useful in validating the optimisated results and checking that improvements have been made and this is especially useful in the absence of a static system-level simulator to validate results.

Interestingly, a significant reduction in average downlink cell load is achieved for the network design formed from random site selections reducing from 1.08 to 0.64 (Figure 7.5). This highlights the effectiveness of the optimisation framework in optimising network designs when sites are not likely to be strategically positioned. The extra improvements made to network designs produced using the pattern-approximation, service-potential-random and service-potential-deterministic algorithms is likely to be a result of effective site selections.

u_d type	Alg	Iteration	e	e_2	e_3	e_4	e_5	e_6	e_7	e_8	e_9
Rur	**p-a**	Initial	**9.578**	0.0000	0.0000	0.3222	2.4504	3.178	1.6858	0.7409	1.2007
		Optimised	**4.8084**	0.0000	0.0000	0.0036	0.1607	3.205	0.4511	0.5167	0.4713
	r-s	Initial	20.2471	0.0000	0.0000	2.0477	4.3987	5.1315	4.5432	1.5659	2.56
		Optimised	11.6204	0.0000	0.0010	0.9245	3.4553	2.9096	1.8559	1.0365	1.4377
	s-p-d	Initial	10.7307	0.0000	0.0001	0.6563	4.2355	2.2067	1.1813	0.8446	1.6061
		Optimised	4.7532	0.0000	0.0000	0.0134	1.0869	1.5732	0.8624	0.4003	0.817
	s-p-r	Initial	13.218	0.0000	0.0000	0.8579	4.6182	3.1731	1.9111	0.9632	1.6946
		Optimised	5.2515	0.0000	0.0000	0.0000	0.7017	2.7297	0.779	0.4716	0.5695
Sub	p-a	Initial	100.1016	0.0016	0.0014	9.0787	34.7877	26.8337	21.0506	2.1913	6.1566
		Optimised	46.3481	0.0016	0.0016	2.282	15.0138	17.0911	8.9373	1.1176	1.903
	r-s	Initial	137.3876	0.0033	0.0037	18.4336	55.2576	28.3952	22.991	4.9116	7.3916
		Optimised	79.4287	0.0122	0.0131	6.1466	33.1673	20.4682	13.8923	1.766	3.963
	s-p-d	Initial	**86.5228**	0.0008	0.0016	11.416	23.8688	23.8213	19.086	4.0599	4.2682
		Optimised	**35.9217**	0.0016	0.0019	1.7514	8.1878	15.7834	7.6224	0.8975	1.6757
	s-p-r	Initial	93.2849	0.0000	0.0004	12.4553	31.1012	23.562	18.147	3.6446	4.3744
		Optimised	40.2331	0.0024	0.0007	2.71	9.8362	16.3688	8.1124	1.1502	2.0524
Urb	p-a	Initial	250.4441	0.0018	0.0011	35.3438	82.4835	63.9718	54.7250	4.8976	9.0195
		Optimised	207.5568	0.0045	0.0040	26.5182	67.6985	57.3578	46.4670	3.8412	5.6656
	r-s	Initial	245.6119	0.0118	0.0102	37.8335	90.1752	57.7263	48.8194	6.2658	4.7699
		Optimised	200.8938	0.0095	0.0074	25.8595	68.7445	54.3048	44.5088	3.6301	3.8292
	s-p-d	Initial	**217.4566**	0.0118	0.0134	30.5650	72.6788	55.9968	47.3764	5.0690	5.7452
		Optimised	**179.6521**	0.0104	0.0102	22.6988	55.7456	53.5398	41.3487	3.5747	2.7239
	s-p-r	Initial	225.8500	0.0091	0.0082	34.7671	76.3596	56.4745	48.7430	3.5624	5.9262
		Optimised	184.4123	0.0132	0.0138	27.1703	57.8429	51.4299	41.5277	2.5010	3.9135

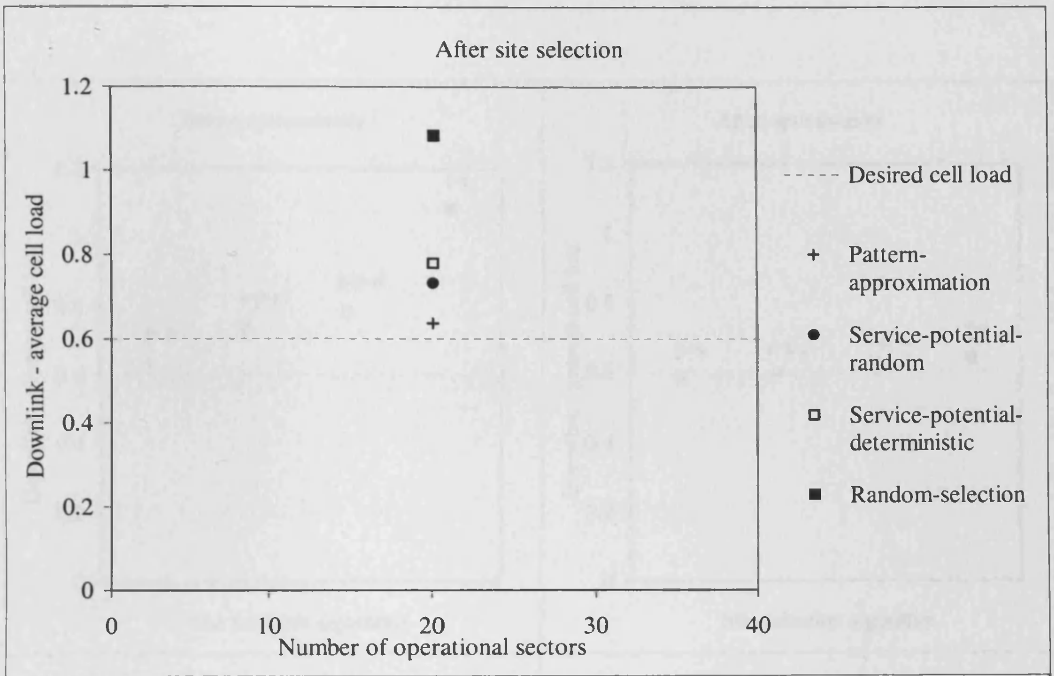
Table 7.3: Optimisation results for network designs where each site is configured with an omnidirectional antenna

u_d	Alg	Solution	Mean	Network	Max	Min	Des	Over	Under	STDEV	Total over $m+d$	% STP	% MS
Rur	p-a	*Initial*	*0.6374*	*12.7479*	*1.3168*	*0.1161*	*2*	*9*	*9*	*0.3043*	*2.4504*	*100*	*100*
		Optimised	0.5891	11.7817	0.7584	0.2871	9	6	5	0.2439	0.1607	100	100
	r-s	Initial	0.5738	11.4757	2.56	0	4	5	11	0.4977	4.3987	100	100
		Optimised	0.6890	13.7805	1.4377	0	4	9	7	0.3614	3.4553	100	99.9
	s-p-d	Initial	0.7789	15.5771	1.6617	0.0556	3	13	4	0.3634	4.2355	100	99.99
		Optimised	0.6078	12.1565	0.9868	0.1698	5	8	7	0.1789	1.0869	100	100
	s-p-r	Initial	0.7311	14.621	1.9079	0.2133	1	9	10	0.3845	4.6182	100	100
		Optimised	0.5987	11.9743	0.9159	0.3464	6	7	7	0.2304	0.7017	100	100
Sub	p-a	Initial	0.7190	74.7795	6.1566	0	5	39	60	0.5417	34.7877	99.84	99.86
		Optimised	0.6652	69.1788	1.9030	0	13	50	41	0.3341	15.0138	99.84	99.84
	r-s	Initial	0.9006	93.6573	7.3916	0	4	41	59	0.8490	55.2576	99.67	99.63
		Optimised	0.7889	82.0490	3.9630	0	8	50	46	0.4969	33.1673	98.78	98.69
	s-p-d	Initial	0.6325	65.7827	4.2682	0	5	38	61	0.5807	23.8688	99.92	99.84
		Optimised	0.6067	63.0991	1.6757	0	25	40	39	0.2741	8.1878	99.84	99.81
	s-p-r	Initial	0.7114	73.9840	4.3744	0	7	37	60	0.5937	31.1012	100.00	99.96
		Optimised	0.6175	64.2150	2.0602	0.0079	20	44	40	0.2918	9.8362	99.76	99.93
Urb	p-a	Initial	0.7097	153.2947	9.0195	0	7	70	139	0.7470	82.4835	99.82	99.89
		Optimised	0.6859	148.1512	5.6656	0	10	83	123	0.5944	67.6985	99.55	99.60
	r-s	Initial	0.7809	168.6734	4.7699	0	8	85	123	0.7758	90.1752	98.82	98.98
		Optimised	0.7037	152.0026	3.8292	0	11	87	118	0.5781	68.7445	99.05	99.26
	s-p-d	Initial	0.7028	151.8139	5.0690	0	12	76	128	0.6509	72.6788	98.8209	98.6600
		Optimised	*0.6531*	*141.0674*	*3.5747*	*0*	*12*	*78*	*126*	*0.5117*	*55.7456*	*98.9569*	*98.9823*
	s-p-r	Initial	0.7094	153.2385	5.9262	0	11	71	134	0.6431	76.3596	99.09	99.18
		Optimised	0.6601	142.5915	3.9135	0	12	74	130	0.5349	57.8429	98.68	98.62

Table 7.4: Downlink network statistics relating to optimisations performed on dimensioned network designs where each site is configured with an omnidirectional antenna

u_d	Alg	Solution	Mean	Network	Max	Min	Des	Over	Under	STDEV	Total over $m+d$
Rur	r-s	Initial	0.4191	8.3827	1.5659	0	1	5	14	0.4717	4.3987
		Optimised	0.4877	9.7547	1.0365	0	4	6	10	0.2966	3.4553
	p-a	Initial	0.417	8.3392	0.8496	0.1086	2	3	15	0.2036	2.4504
		Optimised	0.3875	7.7506	0.6636	0.1469	1	1	18	0.1293	0.1607
	s-p-d	Initial	0.5029	10.0572	0.8971	0.0525	5	4	11	0.2278	4.2355
		Optimised	0.474	9.4799	0.6734	0.2731	5	1	14	0.1148	1.0869
	s-p-r	Initial	0.4568	9.137	1.1314	0.1683	2	4	14	0.262	4.6182
		Optimised	0.4175	8.3501	0.6336	0.162	4	0	16	0.1362	0.7017
Sub	p-a	Initial	0.3923	40.7989	2.1913	0.0000	2	19	83	0.4308	34.7877
		Optimised	0.4238	44.0775	1.1176	0.0000	16	15	73	0.2298	15.0138
	r-s	Initial	0.4712	49.0012	4.9116	0.0000	7	21	76	0.7311	55.2576
		Optimised	0.4315	44.8716	1.7660	0.0000	14	20	70	0.3434	33.1673
	s-p-d	Initial	0.4511	46.9158	4.0599	0.0000	9	22	73	0.5513	23.8688
		Optimised	0.4284	44.5535	0.8975	0.0000	11	17	76	0.2074	8.1878
	s-p-r	Initial	0.4633	48.1872	3.6446	0.0000	10	20	74	0.5388	31.1012
		Optimised	0.4308	44.7989	1.1735	0.0233	12	14	78	0.2235	9.8362
Urb	p-a	Initial	0.4331	93.5398	4.8976	0	8	41	167	0.6936	82.4835
		Optimised	0.4264	92.1032	3.8412	0	14	45	157	0.5345	67.6985
	r-s	Initial	0.4769	103.0092	6.2658	0	13	47	156	0.7134	90.1752
		Optimised	0.4375	94.5007	3.6301	0	17	45	154	0.5128	68.7445
	s-p-d	Initial	0.4551	98.3075	5.7452	0	11	55	150	0.6017	72.6788
	s-p-d	Initial	0.4285	92.5485	2.7239	0	12	51	153	0.4595	55.7456
	s-p-r	Initial	0.4711	101.7477	3.5624	0	7	54	155	0.5970	76.3596
		Optimised	0.4591	99.1564	2.5010	0	10	52	154	0.4955	57.8429

Table 7.5: Uplink network statistics relating to optimisations performed on dimensioned network designs where each site is configured with an omnidirectional antenna



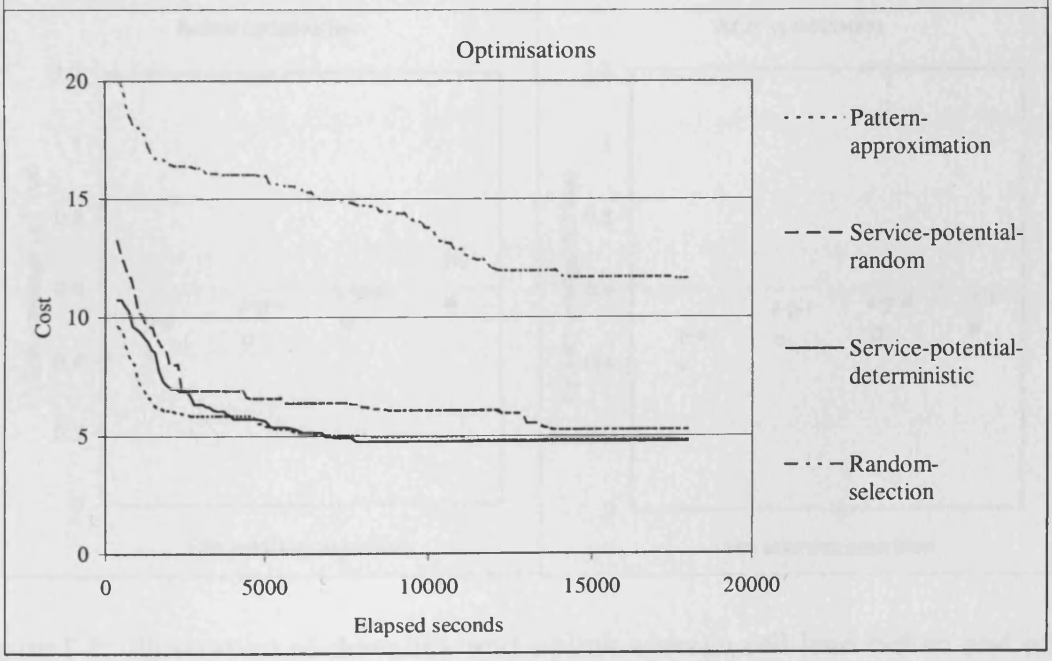


Figure 7.4: Site selection is undertaken using pattern-approximation, service-potential-random, service-potential-deterministic and random-selection algorithms

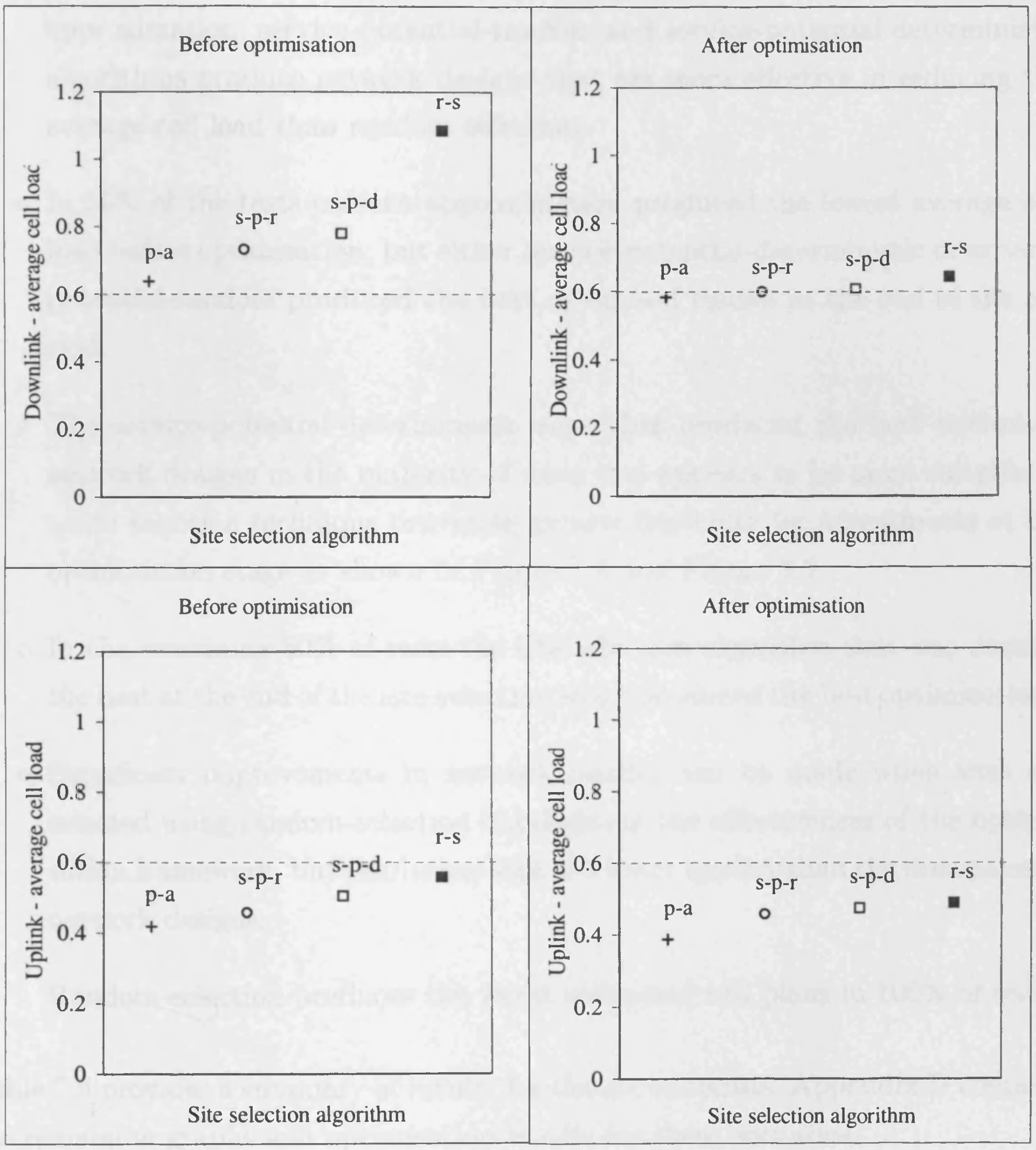


Figure 7.5: Illustration of downlink and uplink average cell load before and after optimisation (rural)

Optimisations are performed for the remaining scenarios the following observations are made:

- In all cases the network designs containing sites selected by either pattern-approximation, service-potential-random and service-potential deterministic algorithms produce network designs that are more effective in reducing the average cell load than random selection.
- In 50% of the tests pattern-approximation produced the lowest average cell load before optimisation, but either service-potential-deterministic or service-potential-random produced the best optimised results at the end of the period.
- The service-potential-deterministic algorithm produced the best optimised network designs in the majority of tests and appears to be more suitable as a site selection technique providing greater flexibility for adjustments at the optimisation stage as shown in Figure 7.6 and Figure 7.7.
- In the remaining 50% of tests the site selection algorithm that was deemed the best at the end of the site selection stage produced the best optimisations.
- Significant improvements in network quality can be made when sites are selected using random-selection highlighting the effectiveness of the optimisation framework, but results are still of a lower quality than the dimensioned network designs.
- Random-selection produces the worst optimised cell plans in 100% of tests.

Table 7.6 provides a summary of results for the six scenarios. Appendix D contains the remaining graphs and optimisation results for these scenarios.

Summary

The dimensioned network designs produced from service-potential-random, service-potential-deterministic and pattern-approximation algorithms all produce optimisations that are more effective than any produced by random selection. In half the cases the algorithm that produced lowest average cell load after site selection also produced the most effective optimisations. In a number of situations the service-potential-deterministic algorithm produces did not produce the lowest average cost at the site selection stage optimisation, but it was capable of producing the best solutions at the end of the optimisation period.

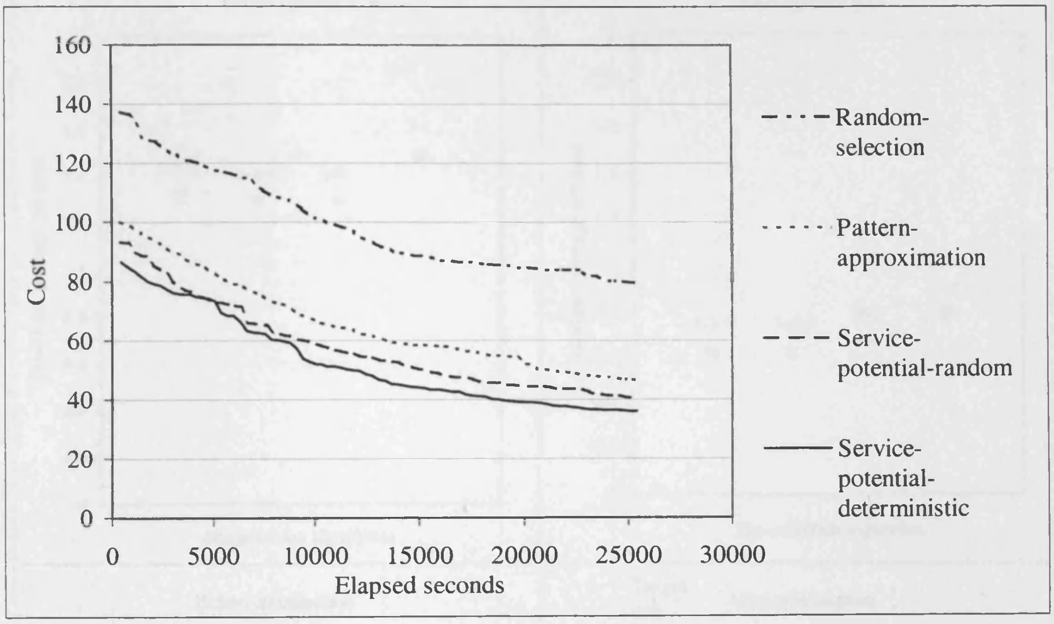


Figure 7.6: Progression of the optimisation for a suburban scenario

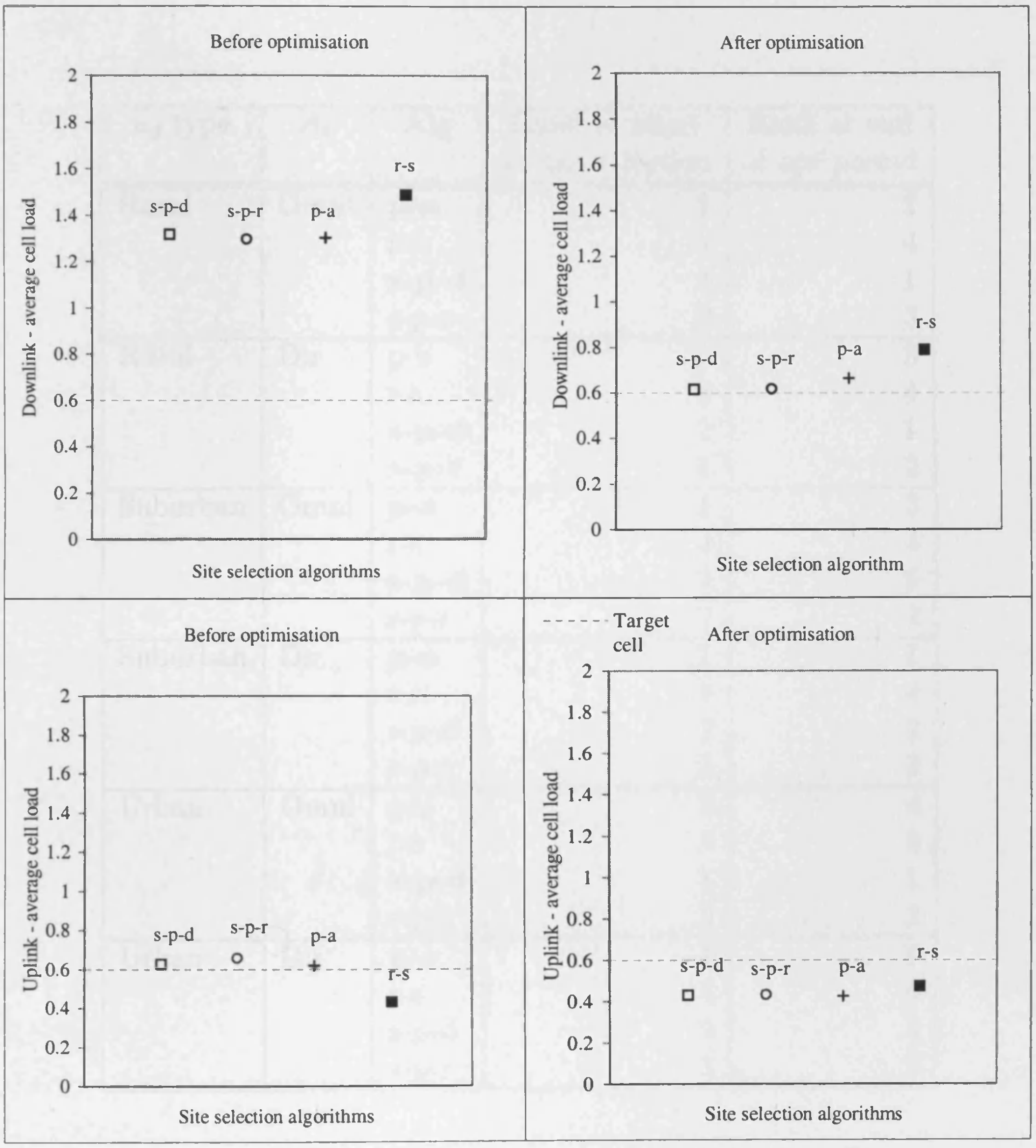


Figure 7.7: Illustration of downlink and uplink average cell load before and after optimisation (suburban)

u_d type	A_k	Alg	Rank of mean at site selection	Rank at end of opt period
Rural	Omni	**p-a**	1	2
		r-s	4	4
		s-p-d	3	1
		s-p-r	2	3
Rural	Dir	p-a	3	3
		r-s	4	4
		s-p-d	2	1
		s-p-r	1	2
Suburban	Omni	**p-a**	1	3
		r-s	4	4
		s-p-d	3	1
		s-p-r	2	2
Suburban	Dir	**p-a**	1	1
		r-s	4	4
		s-p-d	2	2
		s-p-r	3	3
Urban	Omni	p-a	3	4
		r-s	4	3
		s-p-d	1	1
		s-p-r	2	2
Urban	Dir	**p-a**	1	1
		r-s	4	4
		s-p-d	2	3
		s-p-r	3	2

Table 7.6: Summary for uniformly distributed traffic

7.2.2 NON-UNIFORMLY DISTRIBUTED TRAFFIC

When considering non-uniformly distributed traffic, site selections made using service-potential-random and service-potential-deterministic algorithms produce cell plans that are more effective than site selections made randomly or using the pattern-approximation algorithm. This experiment is carried out for six different KORNET1 network design scenarios:

(a) A network design requiring 20 sites, each with a single omnidirectional antenna, required to meet the traffic demand in a rural scenario;

(b) A network design requiring 104 sites, each with a single omnidirectional antenna, required to meet the traffic demand in a suburban scenario;

(c) A network design requiring 216 sites each, each with a single omnidirectional antenna, required to meet the traffic demand in a urban scenario;

(d) A network design requiring 7 sectorised sites for a rural traffic scenario;

(e) A network design requiring 34 sectorised sites for a suburban traffic scenario;

(f) A network design requiring 61 sectorised sites for a urban traffic scenario;

Each of the above network design scenarios are required to meet the traffic demands of non-uniformly distributed mobile station users requiring a mix of voice and multimedia services. Results from a number of these scenarios are discussed specifically in the following paragraphs; the remainder of the results are presented in appendix D.

After site selection was performed considering non-uniform traffic scenarios it was concluded that the average cell load and total network over-loading cannot be used as a measure of performance for the network design alone. From this investigation it was proposed that the standard deviation be considered along with the average cell load when evaluating site selection techniques. In fact the network designs produced from service-potential-deterministic and service-potential-random algorithms had the lowest standard deviation of cell loads and produced the lowest cost network designs during optimisation. Figure 7.8 provides an illustration of the optimisation progress for a suburban traffic scenario. The collection of results for non-uniform traffic scenarios indicates that the algorithm that produces a network design with the lowest standard deviation of cell loads is likely to produce the network design with the lowest cost at the start of optimisation.

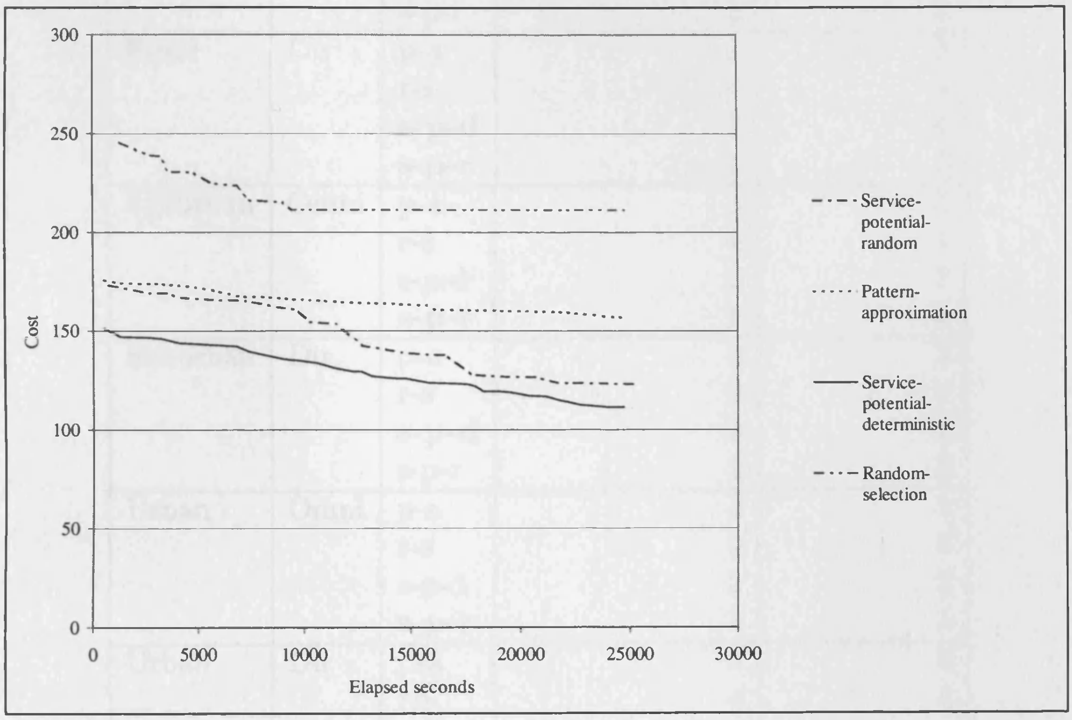


Figure 7.8: Progress of optimisation for a suburban scenario.

From the results of optimisations performed for the remaining scenarios and the following observations can be made:

- Service-potential-deterministic and service-potential-random algorithms appear to be more suitable as site selection techniques providing greater flexibility for adjustments at the optimisation stage as shown in Table 7.7.
- The algorithm with the lowest standard deviation measured at the network dimensioning stage provided the best start to optimisation and optimised solutions with the lowest cost.
- Random-selection produces the worst optimised cell plans in 100% of tests.

u_d type	A_k	Alg	Rank of STDEV at site selection	Rank at end of opt period
Rural	Omni	p-a	3	3
		r-s	4	4
		s-p-d	**1**	**1**
		s-p-r	2	2
Rural	Dir	p-a	3	3
		r-s	4	4
		s-p-d	2	**1**
		s-p-r	**1**	2
Suburban	Omni	p-a	3	3
		r-s	4	4
		s-p-d	2	2
		s-p-r	**1**	**1**
Suburban	Dir	p-a	3	3
		r-s	4	4
		s-p-d	**1**	**1**
		s-p-r	2	2
Urban	Omni	p-a	4	4
		r-s	3	3
		s-p-d	2	2
		s-p-r	**1**	**1**
Urban	Dir	p-a	3	3
		r-s	4	4
		s-p-d	2	2
		s-p-r	**1**	**1**

Table 7.7: Summary for non-uniformly distributed traffic

Summary

Site selections made using service-potential-deterministic and service-potential-random algorithms produce the lowest cost network designs after an optimisation period of five hours. In general, the algorithm that produces the lowest standard deviation of cell loads produces the best start to optimisation when considering non-uniform traffic. Optimisation results obtained when non-uniformly distributed traffic and sites are considered have similar results from which the same conclusions are drawn. Optimisation results produced for scenarios concerning non-uniformly distributed traffic scenarios are presented in appendix D.

7.2.3 REAL WORLD NETWORK DATA SET

This experiment provides an example of the application of the site selection techniques and optimisation framework on a real world data set. The data set has the following characteristics:

- a candidate set containing 244 sites;
- 50225 STP, that is a service area 205 by 245 with a mesh increment of 50 metres;
- 244 sites each configured with an omnidirectional antenna.

A rural traffic scenario is considered and the network is dimensioned using each of the site selection algorithms and results are presented in Table 7.8. The service-potential-deterministic algorithm produces the lowest average cell load and network overloading at the dimensioning stage, closely followed by the service-potential-random algorithm.

Each of the dimensioned network designs is optimised for five hours producing the results in Figure 7.9. A set of benchmark tests is also produced for the best algorithm at the optimisation stage, results are displayed in Table 7.9. The minimum cost obtained for the service-potential-deterministic optimisation (minimum cost 27.1053), was significantly lower than the minimum cost from a benchmark set containing 1185 randomly configured network evaluations (minimum cost 38.1458). This indicates the success of the tabu search optimisation framework. The service-potential-random algorithm produces the lowest cost network design and reduces the cost by on average 49% by the end of the optimisation (see Table 7.10).

The improvements to the quality of the network design made by applying the service-potential-deterministic algorithm are significant after five hours optimising. Although the mean downlink cell load is only slightly reduced from 0.6327 at the dimensioning stage to 0.5639 at the end of the optimisation run-time, during the optimisation significant reduction was made to the range of downlink cell loads. Although, the number of over-loaded cells in the downlink is increased slightly by the service-potential-deterministic algorithm (from 17 to 20), the maximum cell load was reduced from 4.0099 to 1.4091, due to the load being more evenly distributed amongst the cells in the network. Furthermore, the amount

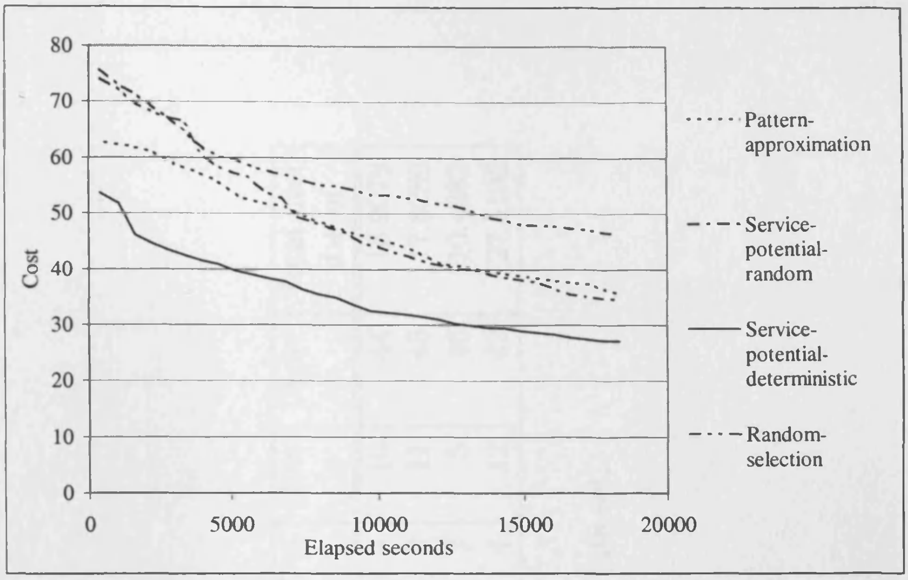


Figure 7.9: Optimisation results for real-world scenario

of network over-loading was significantly reduced from 14.2453 to 4.7254 by the service-potential-deterministic algorithm. These results can be compared to random selection which only manages to reduce the load from 6.5253 to 2.1789. Overall, the service-potential-deterministic algorithm has the highest number of desired cells at the end of the optimisation period. Downlink statistics and uplink statistics relating to these optimisations are listed in Table 7.11 and Table 7.12 respectively. Figure 7.11 displays the uplink and downlink load plans for service-potential-deterministic, showing how the initial site selections make a significant difference to the improvements that can be achieved at the optimisation stage.

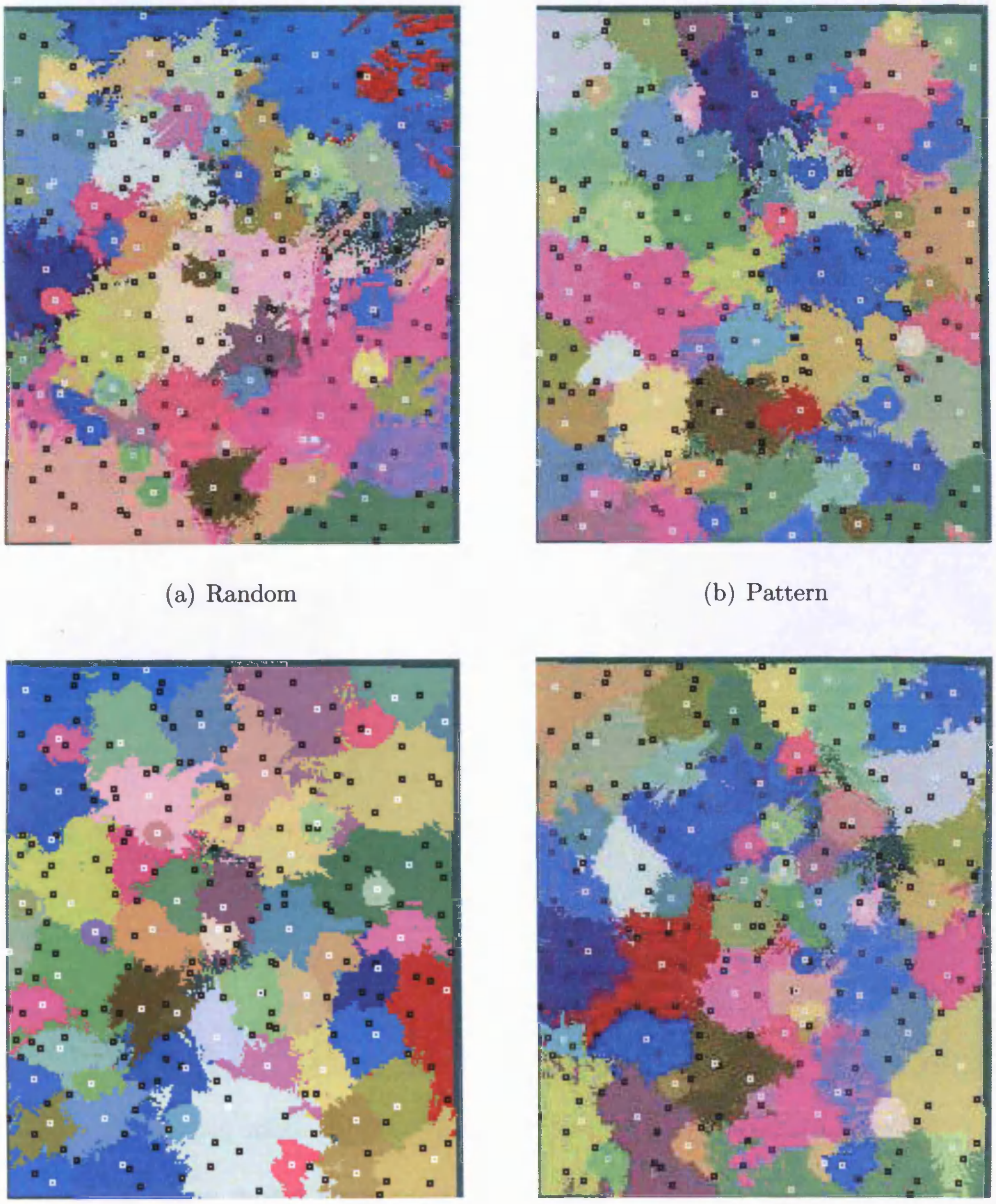
Further experimentation is carried out to determine where the service-potential-deterministic result lies in relation to a set containing 100 network designs produced using random site selection. The network designs produced when applying random site selection also have varying numbers of operational sites (*i.e.* 38 to 78). Figure 7.12 displays these results. In Figure 7.12 it can be seen that site selections made using service-potential-deterministic algorithm have a lower cost than any of the network designs produced using random site selection. Network configuration optimisation is also performed on the lowest cost network design from the random site selection set; however the cost of the service-potential-deterministic, after network configuration optimisation, is lower.

Alg	n_S	n_{op}	Max $\eta_{DL}(c_k)$	Min $\eta_{DL}(c_k)$	Mean $\eta_{DL}(c_k)$	STDEV $\eta_{DL}(c_k)$	Network $\eta_{DL}(c_k)$	Des	Over	Under	Total over $d+m$
p-a	244	58	3.7971	0.0000	0.7403	0.5019	42.9363	4	10	44	18.9079
s-p-d	244	58	3.9796	0.0000	0.6327	0.5084	36.6964	2	11	45	17.8289
s-p-r	244	58	2.3522	0.1084	0.7002	0.3823	40.6093	7	5	46	10.4982
r-s	244	58	4.8298	0.0000	0.8398	0.6464	48.7103	4	12	42	27.5196

Table 7.8: Dimensioning results for real world data set.

Iterations	Max e	Min e	Mean e	STDEV
1185	77.4729	38.1458	56.7486	5.9229

Table 7.9: Benchmark results for real world data set.



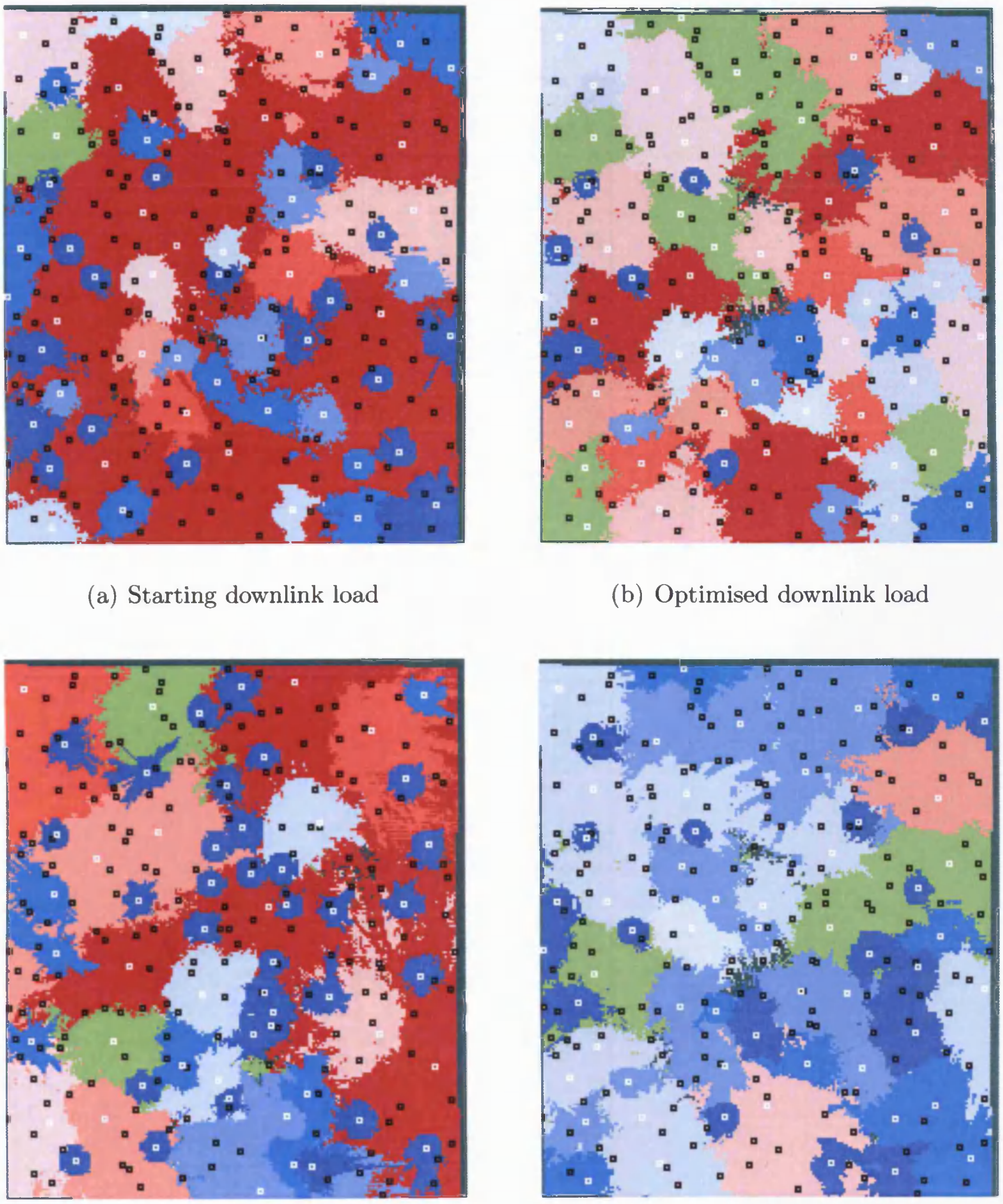
(a) Random

(b) Pattern

(c) Service-potential-deterministic

(d) Service-potential-random

Figure 7.10: Real world data set best server maps



(a) Starting downlink load

(b) Optimised downlink load

(c) Starting uplink load

(d) Optimised uplink load

Figure 7.11: Real world data set - initial and optimised cell plans for a rural scenario

Alg	Solution	e	e_2	e_3	e_4	e_5	e_6	e_7	e_0	e_1
p-a	Initial	74.1448	19.9528	15.2377	4.8538	26.5762	0.0050	0.0398	5.7820	1.6975
	Optimised	46.4001	16.5856	9.8343	2.2247	12.9955	0.0317	0.0532	3.1389	1.5362
r-s	Initial	75.7355	20.0147	18.1294	7.3248	21.0385	0.0017	0.0349	6.5253	2.6661
	Optimised	34.5962	15.0399	8.1338	0.5078	7.7312	0.0117	0.0477	2.1737	0.9506
s-p-d	Initial	53.6048	17.5146	13.1584	2.9689	14.2453	0.0017	0.0356	4.0099	1.6703
	Optimised	27.1053	13.4595	6.3451	0.3003	4.7254	0.0117	0.0408	1.3741	0.8483
s-p-r	Initial	62.7190	18.3680	13.3816	3.5698	20.5452	0.0067	0.0372	4.8333	1.9773
	Optimised	35.5619	14.5825	8.0777	0.1139	10.1553	0.0033	0.0387	1.8307	0.7598

Table 7.10: Optimisation results for a real world data set

Alg	Solution	Mean	Network	Max	Min	Des	Over	Under	STDEV	Total over $d+m$
p-a	Initial	0.2979	17.2793	1.6975	0.0000	1	8	49	0.4311	5.3721
	Optimised	0.3031	17.5784	1.5362	0.0000	3	5	50	0.3143	2.5247
r-s	Initial	0.3385	19.6321	2.6661	0.0000	2	8	48	0.5831	7.8048
	Optimised	0.2988	17.3294	0.9618	0.0112	1	4	53	0.2038	0.7493
s-p-d	Initial	0.3038	17.6213	1.6703	0.0000	2	6	50	0.3435	3.3531
	Optimised	0.3198	18.5502	0.8872	0.0390	3	2	53	0.1736	0.4257
s-p-r	Initial	0.3015	17.4845	1.9773	0.0000	1	8	49	0.3815	4.0498
	Optimised	0.2968	17.2163	0.7598	0.0000	4	2	52	0.1988	0.2814

Table 7.11: Uplink network statistics relating to optimisations performed on dimensioned network designs from the real world data set

Alg	Solution	Mean	Network	Max	Min	Des	Over	Under	STDEV	Total over $d+m$	% STP	% MS
p-a	Initial	0.7740	44.8930	5.7820	0.0000	2	17	39	0.6454	26.5762	99.5000	96.0199
	Optimised	0.6419	37.2317	3.1389	0.0000	6	19	33	0.4643	12.9955	96.8333	94.6819
r-s	Initial	0.6190	35.9023	6.5253	0.0000	3	13	42	0.6481	21.0385	99.8333	96.5077
	Optimised	0.5957	34.5525	2.1789	0.0052	2	29	27	0.3623	7.7312	98.8333	95.2334
s-p-d	Initial	0.5953	34.5270	4.0099	0.0000	1	17	40	0.4522	14.2453	99.8333	96.4420
	Optimised	0.5639	32.7086	1.4091	0.0350	10	20	28	0.3013	4.7254	98.8333	95.9184
s-p-r	Initial	0.7093	41.1401	4.8333	0.0000	4	20	34	0.5611	20.5452	99.3333	96.2827
	Optimised	0.6397	37.1006	1.8307	0.0000	7	27	24	0.3989	10.1553	99.6667	96.1294

Table 7.12: Downlink network statistics relating to optimisations performed on dimensioned network designs from the real world data set

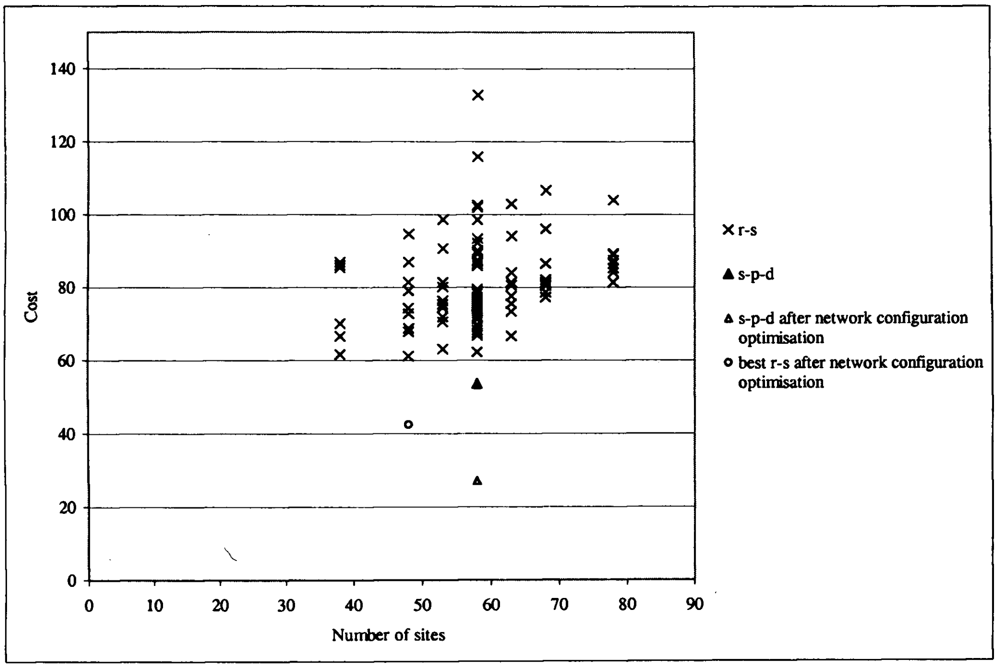


Figure 7.12: Comparison of service-potential-deterministic algorithm with random sample of network designs

7.3 Optimisation results and cell plans

This section looks more specifically at the third stage of the proposed cell planning process (network configuration optimisation) and assesses the optimisations made for a number of the network design scenarios. Consider firstly network design's produced when considering a rural user density environment:

Uniformly distributed traffic and sites: for this scenario the best optimised cell plan was produced by the pattern-approximation algorithm. Initial and optimised cell plans are displayed in Figure 7.13 producing a cell plan with the following characteristics:

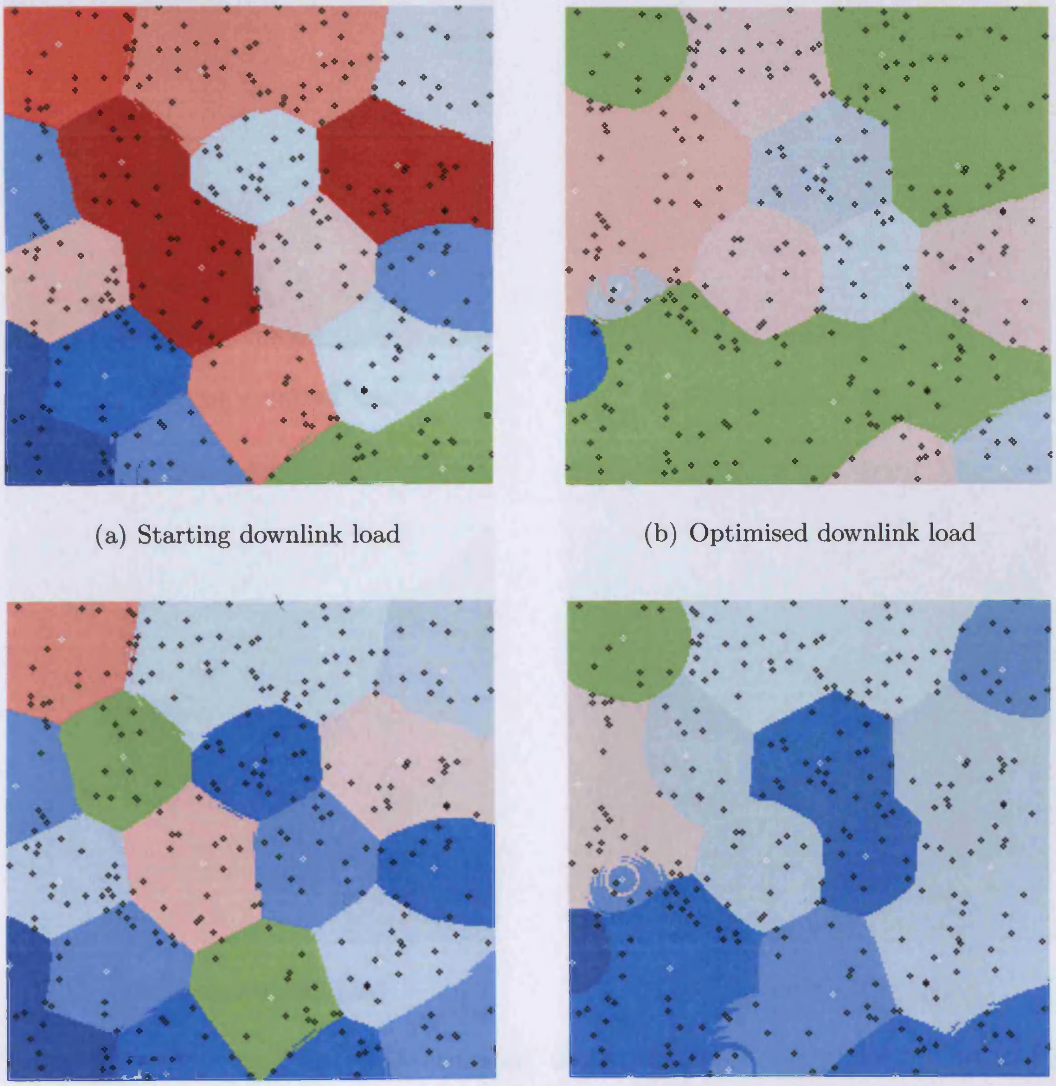
- desired cells were increased from 2/20 to 9/20;
- over-loaded cells were reduced from 9/20 to 6/20;
- over-loaded cells in the optimised cell plan were 30% below the pole-capacity having initially been 10% above the pole capacity;
- the maximum cell load in the downlink was reduced from 1.3168 to 0.7584;
- only one cell was over-loaded in the uplink with a load of 0.6636.

Non-uniformly distributed traffic and uniformly distributed sites: for this scenario the best optimised cell plan was produced by the service-potential-deterministic algorithm. Initial and optimised cell plans are displayed in Figure 7.14 producing a cell plan with the following characteristics:

- desired cells were increased from 0/20 to 6/20;
- even though the number of overloaded cells remained the same the maximum cell load was reduced from 3.0414 to 1.4951;
- average cell load was reduced from 0.7135 to 0.5980;
- only two cells in that group had a cell load over the pole capacity.

Uniformly distributed traffic and non-uniformly distributed sites: for this scenario the best optimised cell plan was produced by the service-potential-deterministic algorithm. Initial and optimised cell plans are displayed in Figure 7.15 producing a cell plan with the following characteristics:

- cells with a desired downlink load were increased from 2/20 to 6/20;
- even though the number of over-loaded sites in the downlink remained the same the maximum cell load was reduced from 3.4528 to 0.7852;
- average downlink cell load was reduced from 0.5718 to 0.5746;
- all cell loads were under the pole capacity.



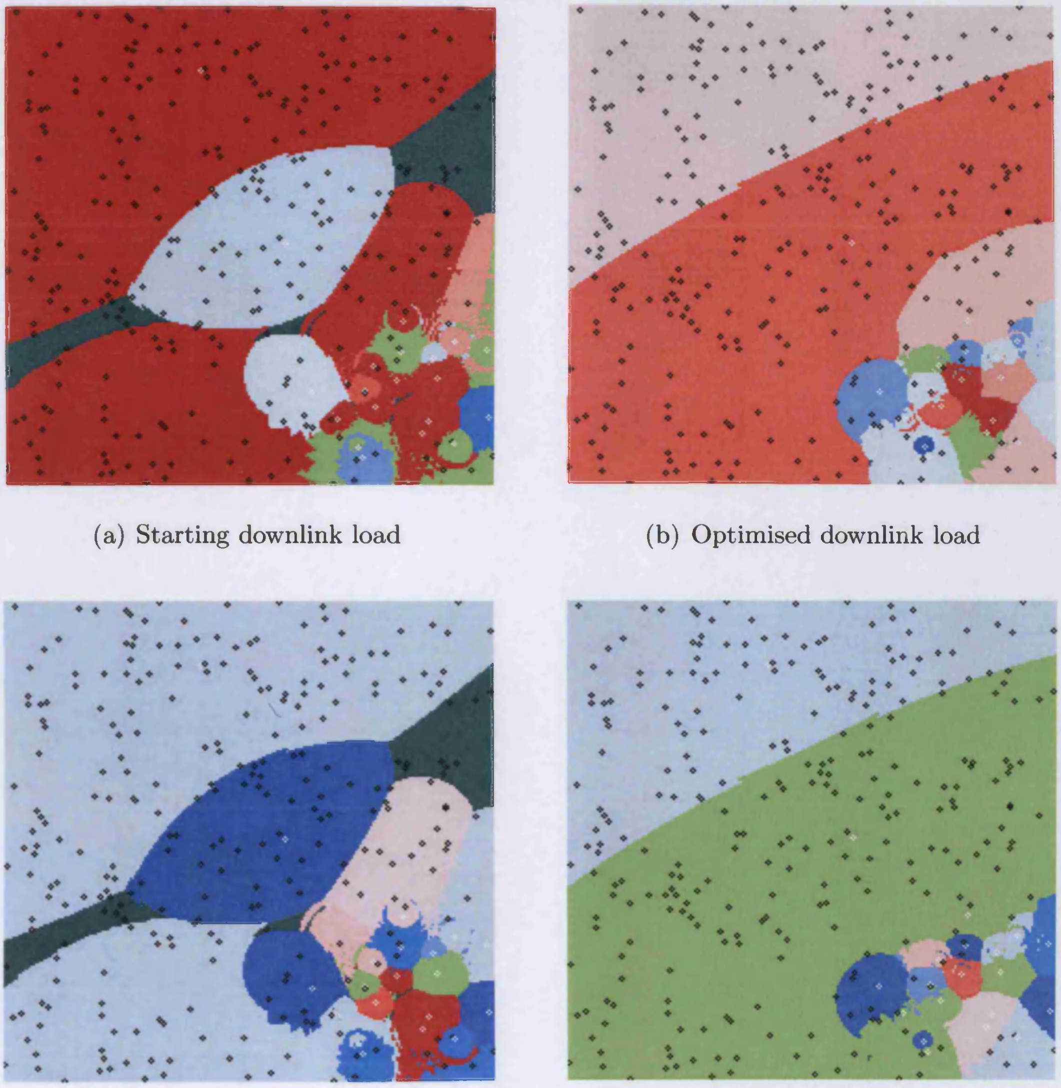
(a) Starting downlink load

(b) Optimised downlink load

(c) Starting uplink load

(d) Optimised uplink load

Figure 7.13: Uniformly distributed traffic and sites - initial and optimised cell plans for a rural scenario



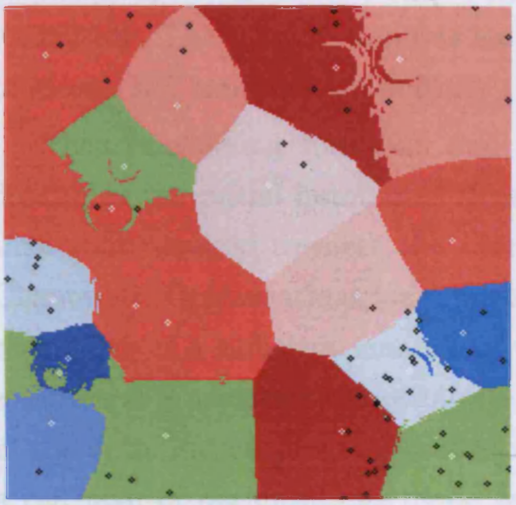
(a) Starting downlink load

(b) Optimised downlink load

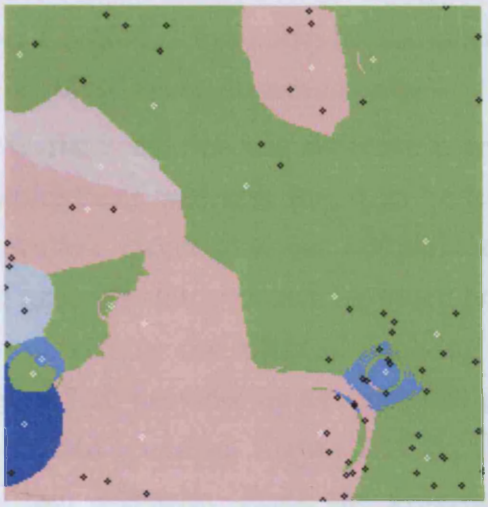
(c) Starting uplink load

(d) Optimised uplink load

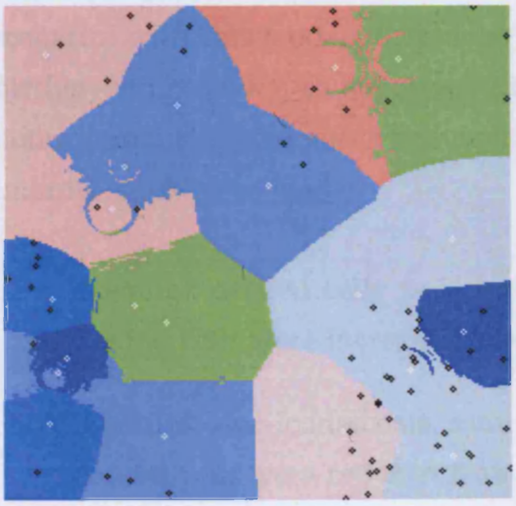
Figure 7.14: Non-uniformly distributed traffic and uniformly distributed sites - initial and optimised cell plans for a rural scenario



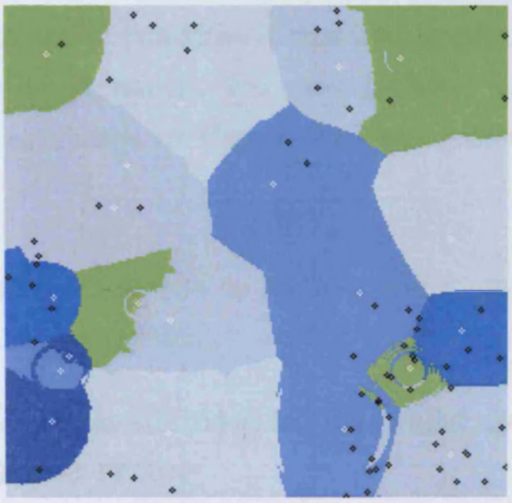
(a) Starting downlink load



(b) Optimised downlink load



(c) Starting uplink load



(d) Optimised uplink load

Figure 7.15: Uniformly distributed traffic and non-uniformly distributed sites - initial and optimised cell plans for a rural scenario

The estimate of the number of sites required for selection seems highly suited to rural scenarios, even though the number of sites suggested for deployment at the network dimensioning stage was below that required to meet the desired average cell load target. Through the application of effective site selection and optimisation techniques significant improvements were made to the network design when optimising. The optimisation was halted after a period of five hours for comparison purposes, but continuation is likely to have involved more improvements.

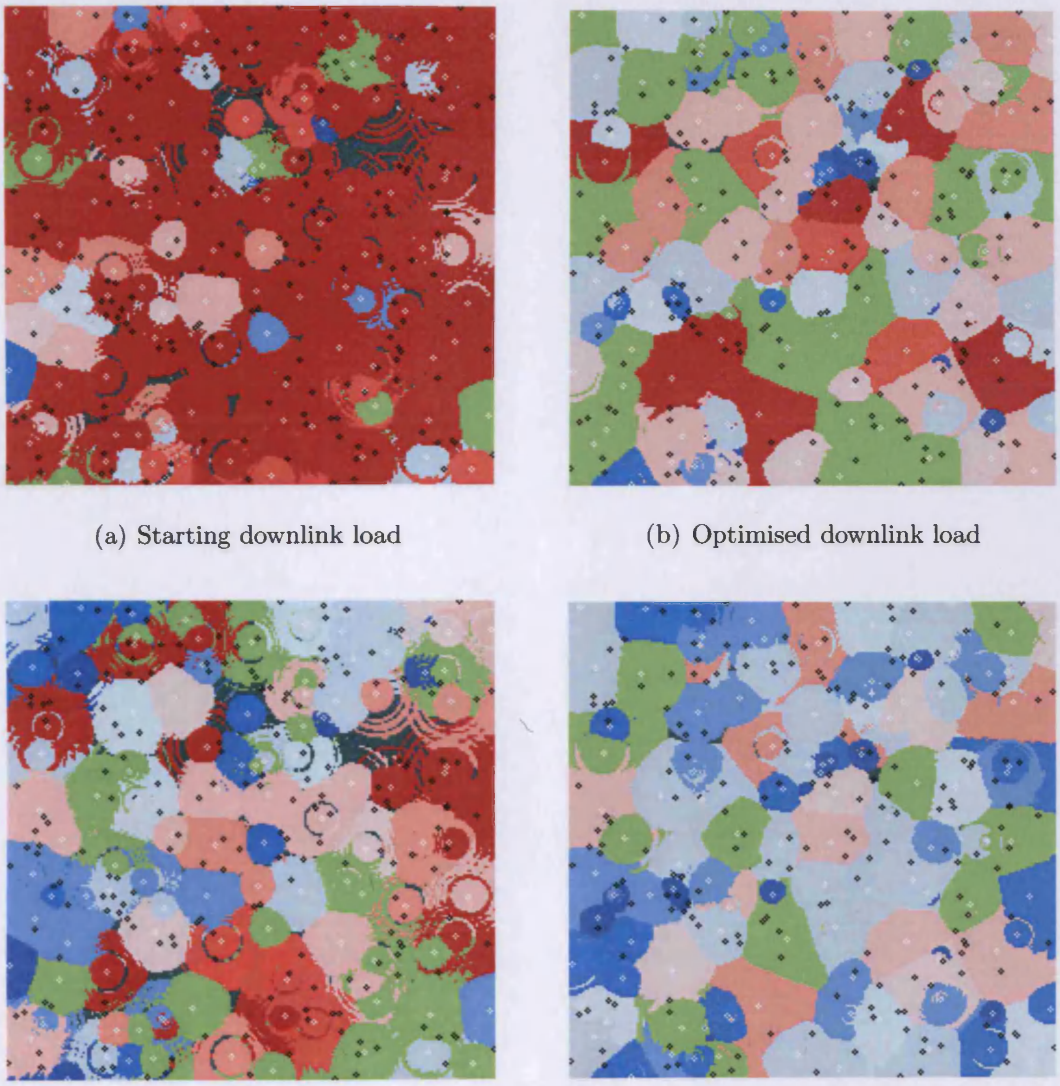
When considering suburban and urban traffic scenarios the estimate used to determine the initial number of sites for deployment was also found to be lower than that required to meet the average downlink target load (as highlighted in Chapter 4). Optimisations for suburban and urban traffic were run for seven hours each. This is a sufficient amount of time to determine the affect of applying site selection as a precursor to optimisation. Figure 7.16 provides an example cell plan of the optimisation progress made for a suburban scenario, Figure 7.17 provides a cell plan of optimisations made for an urban scenario. From the progress of the optimisations made for the network in a suburban environment it is evident that the optimisation framework is suitable for optimising network and traffic scenarios with this model. Increased optimisation run-time is required to produce further optimisations to suburban and urban scenarios. For example after seven hours optimising the suburban scenario as shown in Figure 7.16 the following improvements were made:

- downlink desired cells were increased from 15/104 to 25/104, whilst uplink desired cells were increased from 9/104 to 11/104;
- downlink over-loaded cells were reduced from 40/104 to 38/104, whilst uplink desired cells were reduced from 22/104 to 17/104;
- the maximum cell load in the downlink was reduced from 3.6549 to 1.6757;
- the downlink average cell load was 0.6067;
- the minimum cell load in the downlink remained the same with a zero load.

When optimising the same network for 24 hours the network quality is further improved. This can be seen in Figure 7.18 where the best network designs are compared after seven and 24 hours. Specifically, the following improvements are made to the network design after optimising for 24 hours:

- downlink desired cells were increased from 31/104 to 38/104, whilst uplink desired cells were increased from 9/104 to 15/104;
- downlink over-loaded cells were reduced from 40/104 to 34/104, whilst uplink desired cells were reduced from 22/104 to 9/104;
- Of the over-loaded cells in the downlink and uplink only four were over the pole capacity;
- the maximum cell load in the downlink was reduced from 3.6549 to 1.4129;
- the downlink average cell load was 0.6089 which met the target range;
- the minimum cell load in the downlink remained the same with a zero load.

Therefore an extension of the optimisation run-time is required to produce further improvements to suburban and urban cell plans. Making the tuning recommendations to the estimated number of sites required is also likely to improve the estimate, but obviously involves increasing the number of sites deployed.



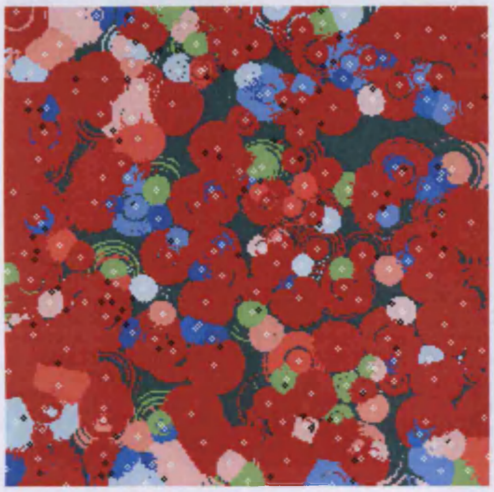
(a) Starting downlink load

(b) Optimised downlink load

(c) Starting uplink load

(d) Optimised uplink load

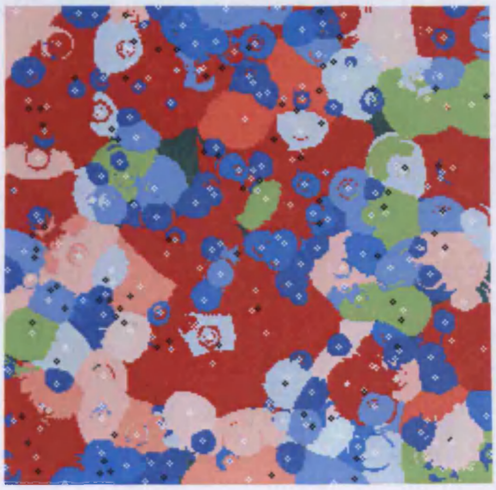
Figure 7.16: Uniformly distributed traffic and sites for a suburban scenario



(a) Starting downlink load

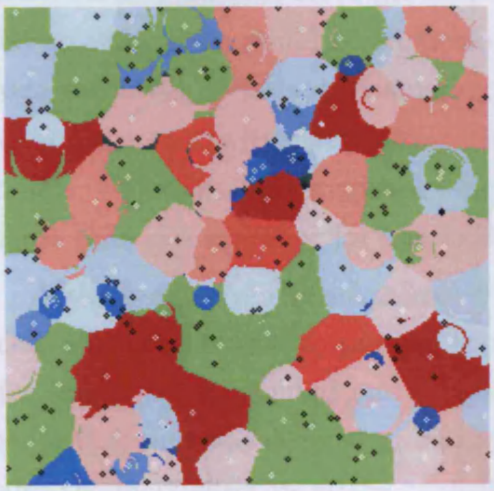
(b) Optimised downlink load

(c) Starting uplink load

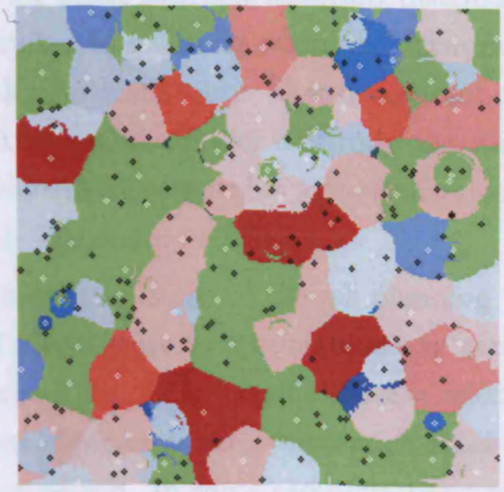


(d) Optimised uplink load

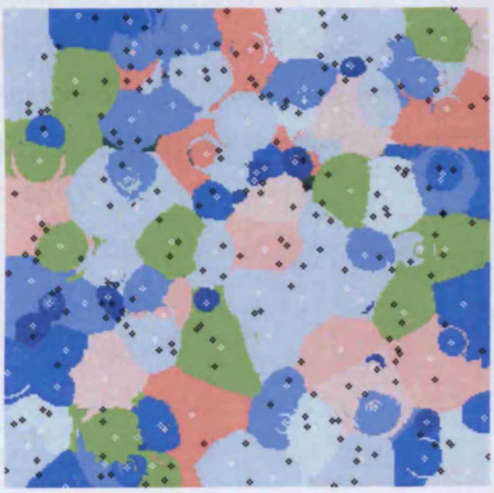
Figure 7.17: Uniformly distributed traffic and sites for an urban scenario



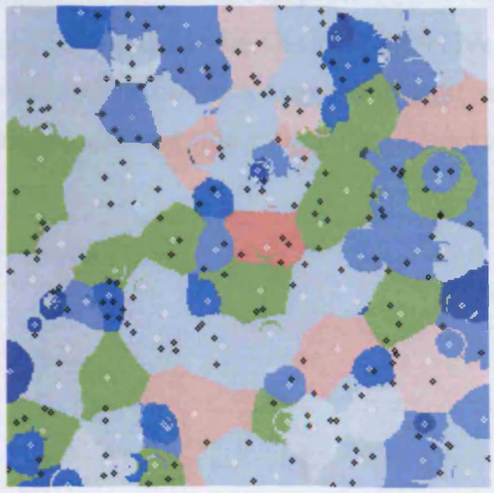
(a) Downlink load - 7 hours



(b) Downlink load - 24 hours



(c) Uplink load - 7 hours



(d) Uplink load - 24 hours

Figure 7.18: Uniformly distributed traffic and sites for a suburban scenario. Optimisations are performed for 24 hours.

7.4 Summary

An investigation into the complexity of the underlying cost function showed that single snapshot evaluation and shared snapshot evaluation are suitable when the network is required to serve one snapshot for traffic that was uniformly distributed. For example, this would be particularly suited to scenarios where the network design was being optimised considering peak hour traffic only. Shared snapshot evaluation was also particularly suited to multiple evaluations for uniformly distributed traffic, whilst multiple snapshot evaluation was more suitable for optimisations of more than one snapshot for non-uniformly distributed traffic.

Making effective site selections is an important stage of the cell planning process and can be used to provide a good initial start to optimisation. In general for uniformly distributed and non-uniformly distributed traffic the site selection algorithm that was deemed to be the most effective at the optimisation stage was also the most effective at the optimisation period. In some cases selections made using the service-potential-deterministic algorithm were not the best at the site selection stage, but during the optimisation made significant improvements. Overall, the service-potential-deterministic algorithm seems to be the most effective site selection technique for use with this optimisation framework suggesting that making site selections according to traffic demand can significantly enhance network quality.

Chapter 8

Conclusions

Network operators desire effective, pragmatic solutions to instances of the cell planning problem to improve the quality of service they provide to their subscribers, enhance their network's coverage and capacity capabilities, and increase company profits. Previous solutions have been designed manually but these methods do not produce the best network configuration. More reliance has since been placed on developing automated cell planning in order to produce more effective solutions to this computationally hard problem, and the introduction of UMTS technology emphasizes the need for high performance planning tools.

The literature review in Chapter 2 showed that many good models and automated solution techniques have been developed and applied to cell planning for a variety of problem scenarios. Omissions in the literature include both the lack of a UMTS model based on Reininger and Caminada's [73] direct modelling approach and the lack of network and traffic data sets for UMTS operational scenarios. This was addressed in Chapter 3 with the contribution of a new UMTS model based on the model developed for a general scenario by Reininger and Caminada [73]. Due to the nature of the cell planning problem it is prudent to investigate any findings in relation to a number of combinations of network and traffic data sets. As the availability of easily accessible data sets is limited, careful consideration has been given to modelling and generating representative data sets based on informed assumptions. It was noted in Chapter 2 that traffic modelling should focus on incorporating UMTS services for a range of user density environments and that methods for distribution should be considered in more detail for predicted data. A suite of data sets was produced based on three addressable markets allowing a number of different traffic scenarios with differing site densities and site distributions to be considered.

Traditionally the cell planning problem has been seen purely as an optimisation problem; however, the pre-operational stage of the cell planning process also involves network dimensioning. Capacity dimensioning has received less attention in the literature than coverage dimensioning and this provided the motivation for incorporating network dimensioning into the solution framework as presented in chapters 4. The main contribution of this thesis is that it demonstrates the possible benefits of applying network dimensioning and site selection optimisation as a precursor to network configuration optimisation and it considers cell planning for the first time in three distinct stages. These stages (consisting of network dimensioning, site selection optimisation and network configuration optimisation), have a versatile application and can be applied separately or as part of a three stage solution framework. Alternatively, the first two stages can be combined as a standalone site estimation tool that provides a rough guide of a network's infrastructure requirements for budgetary purposes.

The first stage of the proposed network dimensioning process was presented in Chapter 4. For the first time a lower bounding technique was utilised to provide an estimate of the number of sites required to meet capacity targets in both the uplink and the downlink. This technique proved to be capable of producing a reasonable estimate of the number of sites required for selection. Certain algorithms can be applied which allow either the best estimate to be selected or one or both of the estimates to be improved upon.

The process for identifying useful sites for deployment in a network is time consuming and can sometimes result in a delay in the network's launch. This issue was addressed in Chapter 5 which concluded the network dimensioning process by investigating a number of methods for performing effective site selections. Three algorithms were presented called service-potential-random, service-potential-deterministic and pattern-approximation with the aim of making effective selections from the set of candidate sites to improve network quality. Overall, results indicated that the proposed selection algorithms produce cell plans that are significantly more effective in improving network quality than selections made at random. Recommendations were made specifying the most appropriate algorithm to apply in a number of measurable operational situations. In particular, service-potential-random and service-potential deterministic algorithms produced cell plans that improved network quality for both uniform and non-uniform traffic scenarios highlighting their the suitability to a variety of traffic scenarios.

To allow an investigation into applying network dimensioning as a precursor to optimisation, an optimisation framework was proposed and presented in Chapter 6. Methods for customising the optimisation framework were provided to allow easy application to a wide range of cell planning scenarios. At this optimisation stage it was determined that effective site selection techniques can provide a good starting network design from which optimisation can start and progress, with the service-potential-deterministic algorithm making the most significant improvements during the optimisation. The three stage solution framework is highly suitable for optimising rural and suburban traffic scenarios for a variety of traffic distribution scenarios, although increased optimisation run-time or estimate tuning is required to produce similar results, to that of rural and suburban, for urban scenarios. Although the automation of cell planning has been well studied the approach employed here is novel, utilising the network dimensioning process to have a positive impact on the network design and optimisation phases of the network planning process. The work presented provides analysis and recommendations that can be adopted to assist the network planning process. The network dimensioning and optimisation algorithms are straightforward and can be implemented in a computationally economic way subject to the size of the network data set under consideration.

8.1 FUTURE WORK

Future work has been discussed briefly in chapters 5 to 6. In general all the techniques described in this thesis can be further developed and employed using models of the operational criteria which are more realistic. This includes using real network data and traffic instances. Application of the network dimensioning process presented in this thesis can be applied, with few adjustments, to a number of different technologies such as GSM networks.

The possibility of improving the assumptions concerning interference in the load factor equations used in network dimensioning should be considered. Also, adding correction factors for dealing with non-uniform traffic and mixed antenna type network designs. Further research into the site selection stage of the presented dimensioning process should concentrate on determining a minimum size of candidate set that should be available, specifying the requirement in terms of site density, from which effective network dimensioning can be performed. Consideration could also be given to using operator specified patterns for experimentation with the pattern-approximation site selection algorithm.

An extension of the optimisation run-time is required to produce further improvements to suburban and urban cell plans. Making the tuning recommendations to the estimated required number of sites is also likely to improve the estimate, but obviously involves increasing the number of sites deployed. The future development of the solution framework could include a final optimisation repair stage to introduce extra sites in any areas of network that are over-loaded.

REFERENCES

[1] Minimum spectrum demand per public terrestrial UMTS operator in the initial phase. Technical Report 5, 2003.

[2] Emile Aarts and Jan Korst. *Simulated annealing and Boltzmann machines: A stochastic approach to combinatorial optimization and neural computing.* John Wiley & Sons, Inc., 1989.

[3] D. Adiego and C. Cordier. Multi-service radio dimensioning for UMTS circuit-switched services. In *proceedings of 54th IEEE Vehicular Technology Conference*, pages 2745–2749, October 2001.

[4] Radiocommunications Agency, date last visited - October 2001. URL `http://www.radio.gov.uk`.

[5] R.G. Akl, M.V. Hedge, M. Naraghi-Pour, and P.S. Min. Cell placement in a CDMA network. *Wireless Communications and Networking Conference*, 2: 903–907, September 1999.

[6] R.G. Akl, M.V. Hedge, M. Naraghi-Pour, and P.S. Min. Multicell CDMA network design. *IEEE Transactions on Vehicular Technology*, 50(3):711–722, May 2001.

[7] S.M. Allen, L. Hodge, S. Hurley, and R.M. Whitaker. Estimating the site requirements for 3G multimedia services. In *proceedings of the 5th IEEE Syposium on Wireless Personal Multimedia Communications*, pages 1202–1206, November 2002.

[8] S.M. Allen, S. Hurley, and R.M. Whitaker. *Methods and Algorithms for Radio Channel Assignment*, chapter 7: Cell planning and network design. Open University Press, 2002.

[9] E. Amaldi, A. Capone, and F. Malucelli. Improved models and algorithms for UMTS radio planning. In *proceedings of the 54th IEEE Vehicular Technology Conference*, volume 2, pages 920 – 924, 2001.

[10] E. Amaldi, A. Capone, and F. Malucelli. Optimizing base station siting in UMTS networks. In *proceedings of the 53rd IEEE Vehicular Technology Conference*, volume 4, pages 2828–2832, May 2001.

[11] H.R. Anderson and J.P. McGeehan. Optimizing microcell base station locations using simulated annealing techniques. In *proceedings of the 44th IEEE Vehicular Technology Conference*, volume 2, pages 858–862, Stockholm, Sweden, 1994.

[12] E. Berruto, M. Gudmundson, R. Menolascino, W. Mohr, and M. Pizarroso. Research activities on UMTS radio interface, network architectures, and planning. *IEEE Communications Magazine*, pages 82–95, February 1998.

[13] G. Bichot, I. Tardy, J. R. Norbury, P. Hirtzlin, J. Lopez L. E. Brten, M. Menozzi, M. Coraggi, G. Auger, S. Nagar, G. F. Vezzani I. Frigyes, M. Schmidt, O. Grndalen, M. Goldhammer, and S. Paillard. Achieving broadband delivery in rural area, EU FP6 broadband services for everyone over fixed wireless access networks (Broadwan) project deliverable D9, 2004.

[14] S. Burley. Capacity of an integrated LCD/UDD WCDMA cellular network. In *proceedings of 3G Mobile Communication Technologies*, number 477, pages A26–A30, March 2001.

[15] S. Burley. Downlink capacity estimations in a WCDMA cellular network. In *proceedings of the 12th IEEE International Symposium on Personal, Indoor and Mobile Radio Communications*, volume 1, pages A–26 – A–30, September 2001.

[16] G. Butt and K. Woodfield. Experiences of Ericsson's WCDMA evaluation system in the UK. In *proceedings of 1st International Conference 3G Mobile Communication Technologies*, number 471, pages 14–18, 2000.

[17] P. Calegari, F. Guidec, P. Kuoen, and D. Wagner. Genetic approach to radio network optimisation for mobile systems. In *proceedings of the 47th IEEE*

Vehicular Technology Conference, volume 2, pages 755–759, Phoenix, USA, May 1997.

[18] N. Cardona and A. Navarro. W-CDMA capacity analysis using GIS based planning tools and Matlab simulation. In *proceedings of 1st International Conference 3G Mobile Communication Technologies*, number 471, pages 230–234, 2000.

[19] I.H. Cavdar and O. Akcay. The optimization of cell sizes and base stations power level in cell planning. In *proceedings of 53rd IEEE Vehicular Technology Conference*, volume 4, pages 2344–2348. IEEE, 2001.

[20] B. Chamaret, S. Josselin, P. Kuonen, M. Pizarroso, B. Salas-Manzanedo, S. Ubeda, and D. Wagner. Radio network optimization with maximum independent set search. In *in proceedings of 47th Vehicular Technology Conference*, volume 2, pages 770–774, May 1997.

[21] J. Créput, A. Koukam, T. Lissajoux, and A. Caminada. Automatic mesh generation for mobile network dimensioning using evolutionary approach. *IEEE Transactions on Evolutionary Computation*, pages 18–30, February 2005.

[22] S. Dehghan, D.Lister, R.Owen, and P.Jones. W-CDMA capacity and planning issues. *Electronics & Communication Engineering Journal*, pages 101–118, June 2000.

[23] Z. Dziong, M. Krishnan, S. Kumar, and S. Nanda. Statistical snap-shot for multi-cell CDMA system capacity analysis. In *Wireless Communications and Networking Conference*, volume 3, pages 1234–1237, September 1999.

[24] A. Eisenblätter, H. Geerdes A. Fügenschuh, D. Junglas, T. Koch, and A. Martin. Integer programming methods for umts radio network planning. In *proceedings WiOpt*, pages 104–111, March 2004.

[25] A. Eisenblätter, H. Geerdes, T. Koch, and U. Türke. Momentum data scenarios for radio network planning and simulation. In *proceedings WiOpt*, pages 433–434, March 2004.

[26] UMTS Forum. 3G offered traffic characteristics. Technical Report 33, 2003.

[27] M. Galota, C. Glasser, S. Reith, and H. Vollmer. A polynomial-time approximation scheme for base station positioning in UMTS networks. In *proceedings of the 5th International workshop on discrete algorithms and methods for mobile computing and communications*, volume 2, pages 52–59, Rome, Italy, 2001.

[28] A. Ganz, C. M. Krishna, D. Tang, and Z. Haas. On optimal design of multitier cellular systems. In *IEEE communications magazine*, pages 88–93, February 1997.

[29] K.S. Gilhousen, I.M. Jacobs, R. Pandovani, A.J. Viterbi, L.A. Weaver, and C.E. Wheatley. On the capacity of the cellular CDMA system. *IEEE Transactions on Vehicular Technology*, 40(2):303–312, May 1991.

[30] F. Glover and M. Laguna. *Modern Heuristic Techniques for Combinatorial Problems*, chapter 3(Tabu search), pages 70–141. McGraw-Hill, 1995.

[31] F. Glover, E. Taillard, and D. de Werra. A user's guide to tabu search. *Annals of Operations Research*, 41(1-4):3–28, 1993. ISSN 0254-5330.

[32] J. Gross and J. Yellen. *Graph Theory and Its Applications.* CRC Press, 1999.

[33] J.K. Han, B.S. Park, Y.S. Choi, and H.K. Park. Genetic approach with a new representation for base station placement in mobile communications. volume 4, pages 2703–2707, October 2001.

[34] S. Hanly and R. Mathar. On the optimal base station density for CDMA cellular networks. *IEEE Transactions on Communications*, 50(8):1274–1281, August 2002.

[35] E. Harroch. Noise rise criterion for the relative performance assessment of multiple CDMA based systems. In *IEE Conference: Getting the most out of the radio spectrum*, 2002.

[36] E. Harroch. Statistical analysis of CDMA-based systems in uplink and applications to FDD and TDD modes coexistance assessment in a regulatory context. In *IEE Conference: Getting the most out of the radio spectrum*, 2002.

[37] M. Hata. Empirical formula for propagation loss in land mobile radio services. *IEEE Transactions on Vehicular Technology*, 29(3):317–325, 1980.

[38] A. Heras-Brandin, P. Bartolome-Pascual, D. Gomez-Mateo, and J. Izquierdo. A multiservice dimensioning procedure for 3G CDMA. In *proceedings of 1st International Conference on 3G Mobile Communication Technologies*, number 471, pages 406–410, 2000.

[39] K. Hiltunen and R. de Bernardi. WCDMA downlink capacity estimation. In *proceedings of the 51st IEEE Vehicular Technology Conference*, volume 2, pages 992–996, May 2000.

[40] John H. Holland. *Adaptation in natural and artificial systems.* MIT Press, 1992.

[41] H. Holma and A. Toskala. *WCDMA for UMTS.* John Wiley & Sons, Chichester, 2000.

[42] S. Hurley. Planning effective cellular mobile radio networks. *IEEE Transactions on Vehicular Technology*, 51(2):243–253, March 2002.

[43] S. Hurley and R. Leese. *Methods and Algorithms for Radio Channel Assignment.* Open University Press, 2002.

[44] L.J. Ibbetson and L.B. Lopes. An automatic site placement algorithm. In *proceedings of 47th IEEE Vehicular Technology Conference*, volume 2, pages 760–764, Phoenix, AZ USA, May 1997.

[45] ILOG CPLEX, date last visited - February 2005. URL `http://www.ilog.com/products/cplex`.

[46] S. Ben Jamaa, Z. Altman, J. Picard, B. Fourestie, and J. Mourlon. Manual and automatic design for UMTS networks. *Mobile Networks and Applications*, 9:619–629, 2004.

[47] R. Kapp-Rawnsley. *Automatic Cell Planning.* PhD thesis, University of Wales Cardiff, 2001.

[48] J. W. Kromer. The use of simplified air interface dimentioning techniques to explain the impact of various UMTS options. In *proceedings of 3rd International Conference on 3G Mobile Communication Technologies*, number 489, pages 281–286, May 2002.

[49] D. Kwon, M. Shin, M. Kim, Y. Yoon, and H.Park. Performance evaluation between CDMA systems by mobile system interference simulator. In *proceedings of IEEE Region 10 Conference*, volume 2, pages 1201–1204. TENCON 99, September 1999.

[50] J. Laiho, A. Wacker, and T. Novosad. *Radio Network Planning And Optimisation For UMTS*. John Wiley & Sons, Chichester, 2002.

[51] J Laiho-Steffens, A. Wacker, and K. Sipilä. Verification of 3G radio network dimensioning rules with static network simulations. In *proceedings of the 51st IEEE Vehicular Technology Conference*, volume 1, pages 478–482, May 2000.

[52] Chae Y. Lee and Hyon G. Kang. Cell planning with capacity expansion in mobile communications: A tabu search approach. *IEEE Transactions on Vehicular Technology*, 49(5):1678–1691, September 2000.

[53] W.C.Y. Lee and D. Lee. CDMA capacity on pathloss and power control. In *proceedings of the 52nd IEEE Vehicular Technology Conference*, volume 2, pages 624–629, September 2000.

[54] M0MENTUM. Capacity and power control for CDMA microcells, September date last visited - 2005. URL `http://momentum.zib.de`.

[55] R. Mathar and T. Niessen. Optimium positioning of base stations for cellular radio networks. *Wireless Networks 6*, 6:421–228, 2000.

[56] R. Mathar and M. Schmeink. Optimal base station positioning and channel assignment for 3G mobile networks by integer programming. *Annals of Operations Research*, 107:225–236, 2001.

[57] A.R. Mishra. *Fundamentals of Cellular Network Planning and Optimisation*. John Wiley & Sons, Ltd, Chichester, England, 2004.

[58] A. Molina, G.E. Athanasiadou, and A.R. Nix. The automatic location of base-stations for optimised cellular coverage: A new combinatorial approach. In *proceedings of 49th IEEE Vehicular Technology Conference.*

[59] A. Molina, G.E. Athanasiadou, and A.R. Nix. Automated W-CDMA micro cellular deployment and coverage reconfiguration based on situation awareness. In *proceedings of the 55th IEEE Vehicular Technology Conference*, pages 1170–1174, 2002.

[60] A. Molina, A.R. Nix, and G.E. Athanasiadou. Optimised base-station location algorithm for next generation microcellular networks. *Electronic Letters*, 36 (7):668–669, March 2000.

[61] D. Molkdar, S. Burley, and J. Wallington. Comparison between simulation and analytical methods of UMTS air interface capacity dimensioning. In *proceedings of 56th IEEE Vehicular Technology Conference*, volume 3, pages 1596–1601, September 2002.

[62] Ofcom Office of Communications, date last visited - July 2004. URL `http://www.ofcom.org.uk`.

[63] Y. Okumura, E. Ohmori, T. Kawano, and K. Fukuda. Field strength and its variability in the VHF and UHF land mobile service. *Review Electronic Communication Lab*, 16(9-10):825–873, 1968.

[64] B. Olin, H. Nyberg, and M. Lundevall. A novel approach to WCDMA radio network dimensioning. In *proceedings of the 60th IEEE Vehicular Technology Conference*, Los Angeles, California, September 2004.

[65] K.E. Oliver, S. Hurley, and S.M. Allen. In *proceedings of PGNET 2002*, Liverpool, UK, July 2002.

[66] K.E. Oliver, S. Hurley, and S.M. Allen. Utilising network dimensioning to improve automated cell planning. In *proceedings of the 60th IEEE Vehicular Technology Conference*, pages 3419–3423, Los Angeles, California, September 2004.

[67] K.E. Oliver, S. Hurley, and S.M. Allen. *ACM Crossroads Magazine*, August 2005.

[68] R. Owen, S. Burley, P. Jones, and V. Messer. Considerations for UMTS capacity and range estimations. *Capacity and Range Enhancement Techniques for the Third Generation Mobile Communications and Beyond*, pages 5/1 – 5/6, February 2000.

[69] D. T. Pham and D. Karaboga. *Intelligent optimization techniques.* Springer, London, 2000.

[70] R. Kapp Rawnsley and S. Hurley. Towards automatic cell planning. In *proceedings of 11th IEEE International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC)*, volume 2, pages 1583–1588, September 2000.

[71] C.R. Reeves, editor. *Modern Heuristic Techniques for Combinatorial Problems.* McGraw-Hill, 1995.

[72] P. Reininger and A. Caminada. Connectivity management on mobile network design. In *proceedings of the 10th Conference of the European Consortium for Mathematics in Industry (ECMI-98)*, Goteborg, Sweden, 1998.

[73] P. Reininger and A. Caminada. Model for GSM radio network optimization. *ACM Interational Conference for Discrete Algorithms and Methods for Mobility*, 1998.

[74] P. Reininger, T. Dony, and A. Caminada. Mobile cellular network evaluation: The cover. *High Performance Computing*, pages 242–247, 1998.

[75] Hugo Santos Pinto. UMTS radio interface roll out aspects. *IEEE Society News*, August 2001.

[76] J. Shapira. Microcell engineering in CDMA cellular networks. *IEEE Transactions on Vehicular Technology*, 43(4):817–825, November 1994.

[77] J. Shapira and R. Padovani. Spacial topology and dynamics in CDMA cellular radio. In *proceedings of the 42nd IEEE VTS*, pages 213–216, Denver, May 1992.

[78] S. Sharma, E. Tameh, A. Molina, and A.R. Nix. Automated W-CDMA microcellular deployment and coverage reconfiguration based on situation aware-

ness. In *proceedings of 55th IEEE Vehicular Technology Conference*, volume 3, pages 1170–1174, May 2002.

[79] K. Sipila, K.-C. Honkasalo, J. Laiho-Steffens, and A. Wacker. Estimation of capacity and required transmission power of WCDMA downlink based on a downlink pole equation. In *proceedings of the 51st IEEE Vehicular Technology Conference*, pages 1002–1005, May 2000.

[80] C. Smith and D. Collins. *3G Wireless Networks.* McGraw-Hill, 2002.

[81] A. Spilling and A. Nix. Network planners face more challenges with UMTS. *Wireless Europe*, 2001.

[82] P. Stevens. Operator design and planning issues for UMTS networks. *The Institution of Electrical Engineers.*

[83] R. Taplin. Scenario generator software. School of Computer Science Cardiff University.

[84] K. Tutschku and P. Tran-Gia. Spacial traffic estimation and characterization mobile communication network design. *IEEE Journal on Selected Areas in Communication*, 16, June 1998.

[85] K. Tutschuka, K. Leibnitz, and P. Tran-Gia. ICEPT an integrated cellular network planning tool. In *proceedings of 47th IEEE Vehicular Technology Conference*, volume 2, pages 765 – 769. IEEE, May 1997.

[86] Michel Vasquez and Jin-Kao Hao. A heuristic approach for antenna positioning in cellular networks. *Journal of Heuristics*, 7(5):443–472, 2001. ISSN 1381-1231.

[87] A. Wacker, J. Laiho-Steffens, K. Sipilä, and M. Jasberg. Static simulator for studying WCDMA radio network planning issues. In *proceedings of the 49th IEEE Vehicular Technology Conference*, volume 3, pages 2436–2440. IEEE, May 1999.

[88] L. Walters and P.S. Kritzinger. Cellular networks: Past, present and future. *Crossroads the ACM Student Magazine for Mobile and Wireless Computing*, 7.2, 2002.

[89] R. Whitaker and S. Hurley. *Telecommunications Network Design and Management*, chapter 2, pages 25–41. Kluwer Academic Publishers, Netherlands, 2002.

[90] R.M. Whitaker and S. Hurley. On the optimality of facility location for wireless transmission infrastructure. *Computers & Industrial Engineering*, 46(1): 171–191, 2004.

[91] J.F. Whitehead. Cellular system design: An emerging engineering discipline. *IEEE Communications Magazine*, 24(2):9–15, 1986.

[92] J.K.L. Wong, M.J. Neve, and K.W. Sowerby. Optimisation strategy for wireless communications system planning using linear programming. *IEEE Electronic letters*, 37(17):1086–1087, 2001.

[93] S. Yang. *CDMA RF System Engineering.* Artech House Publishers, 1998.

[94] Q. T. Zhang. Bridge the gap between dynamic and static methods for cell planning. *IEEE Transactions on Vehicular Technology*, 50(5):1224–1230, September 2001.

[95] H. Zhu, T. Buot, R. Nagaike, and S. Harmen. Load balancing in WCDMA systems by adjusting pilot power. In *5th International Symposium on Wireless Personal Communications*, volume 3, pages 936–940, October 2002.

Appendix A

Signal, Carriers and Power

Electromagnetic waves are capable of travelling long distances and this property makes them suitable for use in a communication system. Information that can be conveyed through such a system is called a *signal.* A *carrier* is a radio wave with a set frequency that can be modulated in order to transmit a signal.

The power of a signal is often measured in Watts (W) where

$$1 \text{ Watt} = 1 \text{ joule per second}$$

The decibel (dB) is the unit used to express relative signal strength. It is expressed as the base ten logarithm of the ratio of the powers of two signals. For two quantities P_0 and P_1 their ratio in terms of decibels is defined as

$$10 \log_{10} \left(\frac{P_0}{P_1} \right)$$

Logarithms are useful as the unit of measurement as signal power tends to span several orders of magnitude and signal losses and gains can be expressed in terms of subtraction and addition. To convert x Watts into decibels, consider the ratio of x Watts relative to 1 Watt

$$x \text{ Watts} = 10 \log_{10} x \text{ dB}$$

Often dB ratios are expressed using a third letter (or more), i.e. dBm, dBi. The extra letters are a reference level for the log operation. For instance, dBm is used to define dB levels with respect to a milliwatt. This can be used for representing the power setting of an antenna

$$x \text{ Watts} = 10 \log_{10} 10^3 x \text{ dBm}$$

APPENDIX B

EXTRA SITE SELECTION ALGORITHM

When selecting sites using the service-potential-random algorithm, after the square has been positioned correctly over the site the number of mobile station users that fall within the boundaries of the square can be counted and recorded. It is important at this point to remove the mobile station users that are covered by the site from the set of all mobile station users. If this step is not performed network designs are produced, which normally involve the majority of sites being clustered in the same area producing network designs with high network overloading and higher average cell loads than those generated when random site selection is performed. The table B.1 includes the site selection results attained when the mobile stations are not removed.

Data	A_k	u_d	n_{op}^S	n_{op}	Max $\eta_{DL}(c_k)$	Min $\eta_{DL}(c_k)$	Mean $\eta_{DL}(c_k)$	STDEV $\eta_{DL}(c_k)$	Network $\eta_{DL}(c_k)$	Des	Over	Under	Total over $d+m$
Stepping-up													
K1	Omni	Rur	20	20	6.7406	0.0000	1.2753	1.0409	25.5064	1	6	13	15.6830
		Sub	104	104	4.5268	0.0000	1.3773	0.8621	143.2366	15	40	49	85.2681
		Urb	216	216	5.0120	0.0000	1.1557	0.7241	249.6337	38	59	119	137.8622
K1	Dir	Rur	7	21	6.1623	0.0000	1.5868	1.2940	33.3232	1	8	12	24.7334
		Sub	38	114	7.3907	0.0000	1.1461	2.9246	130.6512	10	24	80	81.9929
		Urb	67	201	11.3666	0.0000	1.2100	0.8459	243.2079	15	59	127	143.1796
K2	Omni	Rur	42	42	5.1599	0.0000	1.2772	0.8507	53.6438	2	16	24	31.9440
		Sub	216	216	8.4996	0.0000	1.4023	0.9111	302.9023	28	85	103	179.4164
		Urban	460	460	5.1950	0.0000	1.1139	0.8572	512.3927	65	120	275	272.1742
K2	Dir	Rur	14	42	23.9575	0.0000	1.8257	2.5570	76.6791	0	8	34	66.0972
		Sub	80	240	21.9002	0.0000	1.1310	2.3584	271.4516	14	50	176	170.9021
		Urb	143	429	12.3651	0.0000	1.1627	1.1467	498.7892	37	115	277	296.1736
Stepping-down													
K1	Omni	Rur	20	20	6.7406	0.0000	1.2753	1.0409	25.5064	1	6	13	15.6830
		Sub	85	85	6.9237	0.0000	1.6961	1.1406	144.1701	11	37	37	96.7129
		Urb	168	168	7.7205	0.0000	1.5285	0.9633	256.7858	25	75	68	161.7581
K1	Dir	Rur	7	21	6.1623	0.0000	1.5868	1.2940	33.3232	1	8	12	24.7334
		Sub	33	99	12.6329	0.0000	1.3414	0.9494	132.7968	7	28	64	87.3746
		Urb	56	168	3.5240	0.0000	1.1290	0.6026	189.6770	17	72	79	92.0814
K2	Omni	Rur	38	38	13.7800	0.0635	1.5869	1.2905	60.3023	2	18	18	40.0784
		Sub	168	168	13.7948	0.0000	1.8096	1.2162	304.0077	17	85	66	204.0096
		Urb	340	340	5.5830	0.0000	1.5362	1.0645	522.3195	56	153	131	323.5638
K2	Dir	Rur	700	14	23.9575	0.0000	1.8257	2.5570	76.6791	0	8	34	66.0972
		Sub	67	201	21.1647	0.0000	1.3513	1.0672	271.6065	10	44	147	183.0815
		Urb	120	360	12.0716	0.0000	1.2982	0.8975	467.3683	24	130	206	281.4437

Table B.1: Site selection results obtained when the mobile stations are not removed.

Appendix C

Hexagonal Pattern Generation

In a hexagon all six sides have the same length u that meet at an angle of 120°. All other dimensions of the hexagon can be calculated from knowing u or χ, so by setting u or χ all the missing information can be calculated. Given distance χ as shown in figure C.1, the height h and side u can be calculated by use of the following formulae

$$\begin{aligned} u &= \frac{\chi}{\cos 30} \\ h &= u \sin 30 \end{aligned}$$

If the row is an even row (assuming zero is even) then the following formula is used to calculate the x coordinate of the desired site:

$$\text{x coordinate for even row} = \texttt{xIndex} \times 2\chi - \chi$$

However, if the row is odd the formula is changed to

$$\text{x coordinate for odd row} = \texttt{xIndex} \times 2\chi - 2\chi$$

The y coordinate of the desired point is defined as:

$$\text{y coordinate} = h + s \times \texttt{yIndex}$$

If `xIndex` $= 1$ and `yIndex` $= 0$ then the point labelled $D1$ in the graph in figure 5.7 is obtained. The point is added to a list of desired site locations and `xIndex` is incremented. This process is repeated until `xIndex` is greater than the width of the service area `xDirection`), at which point `xIndex` is reset to 0. Next, `yIndex` is incremented producing a new point, which is added to the list of desired site locations. This process is repeated until `xIndex` is greater than the height of the service area `yDirection`).

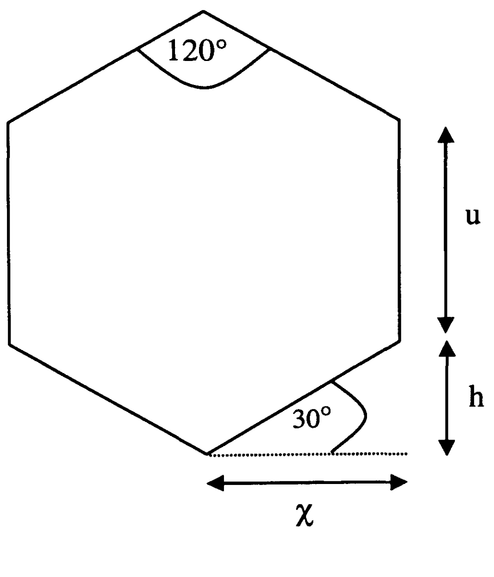


Figure C.1: Generating a hexagonal pattern. In a hexagon all six sides have the same length s that meet in an angle of 120°. All other dimensions of the hexagon can be calculated from knowing u or χ, so by setting u or χ all the missing information can be calculated

APPENDIX D

PRECURSOR

This appendix contains optimisation results and network statistics for the scenarios that were summarised in chapter 7.

Optimisation results for network designs where all the sites have associated omnidirectional antenna and consider uniformly distributed traffic are displayed in table D.1. Network statistics associated with these optimisation results can be found in table for the downlink D.2 and table D.3 for the uplink.

- a graph showing the progress of the optimisation for a rural scenario can be seen in figure D.1;
- a graph showing the progress of the optimisation for a suburban scenario can be seen in figure D.2;
- a graph showing the progress of the optimisation for a suburban scenario can be seen in figure D.3.

u_d	Alg	Solution	e	e_2	e_3	e_4	e_5	e_6	e_7	e_8	e_9
Rur	r-s	Initial	26.9552	0.0000	0.0000	3.0443	4.5144	6.9269	6.9379	2.3547	3.1770
		Optimised	17.2056	0.0000	0.0000	2.3523	3.4483	4.0025	4.5111	1.3880	1.5035
	p-a	Initial	20.9622	0.0000	0.0000	0.9549	6.9320	5.2193	4.8026	0.9940	2.0593
		Optimised	8.1000	0.0041	0.0021	0.6706	0.9035	3.0703	1.5152	0.9438	0.9903
	s-p-d	Initial	22.2339	0	0	1.6739	5.2289	5.5858	5.0040	1.5430	3.1983
		Optimised	5.9923	0	0	0.0251	0.9314	2.6748	1.1025	0.5790	0.6796
	s-p-r	Initial	23.3304	0.0000	0.0000	2.0815	4.0458	6.4907	5.6953	2.3115	2.7055
		Optimised	7.3479	0.0000	0.0000	0.0940	1.3359	2.8892	1.3524	0.6804	0.9960
Sub	p-a	Initial	102.0535	0	0	9.9801	26.8334	29.7349	24.7695	6.9033	3.8322
		Optimised	67.3576	0	0.0001	3.3987	14.2255	27.0174	19.7905	1.7769	1.1484
	r-s	Initial	167.8841	0	0.0001	28.2724	49.3775	36.9263	33.1279	10.2	9.9799
		Optimised	110.873	0	0.0005	10.5007	31.2646	32.8127	28.584	4.7724	2.9381
	s-p-d	Initial	114.9075	0	0.0001	12.0197	34.8733	32.9855	27.0169	5.0553	2.9568
		Optimised	69.9747	0	0.0007	3.5682	19.1382	25.68	17.8347	2.6623	1.0905
	s-p-r	Initial	122.5059	0.0016	0.001	9.9565	46.1451	31.9643	26.6799	5.6748	2.0826
		optimised	77.2629	0	0.0001	4.7167	18.7101	27.774	22.0457	2.4171	1.5991
Urb	r-s	Initial	234.1975	0.0009	0.0016	27.8836	80.3059	60.9254	52.4399	4.4120	8.2282
		Optimised	282.3504	0.0005	0.0001	48.8774	94.7131	62.3754	55.7716	7.6333	12.9791
	p-a	Initial	191.2016	0.0027	0.0023	18.2184	61.6948	55.7274	44.7914	3.7418	7.0228
		Optimised	162.9753	0.0005	0.0008	13.2778	51.5405	51.8318	40.5168	2.0607	3.7465
	s-p-d	Initial	202.6891	0.0009	0.0027	26.1781	63.8442	53.6061	44.5204	6.4746	8.0621
		Optimised	187.7094	0.0009	0.0025	23.2972	60.6634	50.6892	39.7728	6.4746	6.8088
	s-p-r	Initial	239.0732	0.0018	0.0012	49.7461	65.0424	52.6421	42.4086	24.2050	5.0260
		Optimised	169.0618	0.0023	0.0031	16.2859	57.6131	49.5169	39.5264	2.2575	3.8567

Table D.1: Optimisation results for network designs where each site is sectorized (uniformly distributed traffic and sites)

u_d	Alg	Solution	Mean	Network	Max	Min	Des	Over	Under	STDEV	Total over $m+d$	%STP	% MS
Rural	r-s	Initial	0.4550	9.5559	3.1770	0.0000	2	4	15	0.6446	4.5144	100	100
		Optimised	0.5294	11.1172	1.5035	0.0000	0	7	14	0.4377	3.4483	100	100
	p-a	Initial	0.6931	14.5550	2.0593	0.0000	1	9	11	0.4683	6.9320	100	100
		Optimised	0.5601	11.7630	1.1023	0.1119	3	7	11	0.2646	0.9035	99.59	99.79
	s-p-d	Initial	0.5831	12.2444	3.1983	0	3	4	14	0.4739	5.2289	100	100
	s-p-r	Initial	0.4943	10.3798	2.7055	0.0000	2	5	14	0.5480	4.0458	100	100
		Optimised	0.5972	12.5405	1.0611	0.0650	7	7	7	0.2483	1.3359	100	100
	p-a	Initial	0.6016	68.5820	6.9033	0	3	40	71	0.5617	26.8334	100.00	100.00
		Optimised	0.5378	61.3077	1.7769	0	17	36	61	0.3330	14.2255	100.00	99.99
	r-s	Initial	0.7143	81.4254	10.2000	0	5	28	81	1.1597	49.3775	100.00	99.99
		Optimised	0.6040	68.8590	4.7724	0	5	36	73	0.5352	31.2646	100.00	99.95
	s-p-r	Initial	0.7515	85.6736	5.6748	0	6	36	72	0.5853	46.1451	99.84	99.90
		Optimised	0.5555	63.3255	2.4171	0	9	38	67	0.3764	18.7101	100.00	99.99
	s-p-d	Initial	0.6481	73.8874	5.0553	0	8	32	74	0.5831	34.8733	100.00	99.99
		Optimised	0.6083	69.3455	2.6623	0	13	47	54	0.3694	19.1382	100.00	99.93
Urban	r-s	Initial	0.7152	143.7526	8.2282	0	10	56	135	0.7219	80.3059	99.91	99.84
		Optimised	0.7697	154.7053	12.9791	0	9	56	136	1.0944	94.7131	99.95	99.99
	p-a	Initial	0.6653	133.7236	7.0228	0	12	65	124	0.5606	61.6948	99.73	99.77
		Optimised	0.6415	128.9458	3.7465	0	14	70	117	0.4638	51.5405	99.95	99.92
	s-p-d	Initial	0.6789	136.4539	8.0621	0	10	65	126	0.7103	63.8442	99.91	99.73
		Optimised	0.6887	138.4194	6.8088	0	12	68	121	0.6545	60.6634	99.91	99.75
	s-p-r	Initial	0.6975	140.2032	5.0260	0	11	68	122	1.7834	65.0424	99.82	99.88
		Optimised	0.6791	136.5073	3.8567	0	8	77	116	0.4942	57.6131	99.77	99.69

Table D.2: Downlink network statistics relating to optimisations performed on dimensioned network designs where each site is sectorized (uniformly distributed traffic and sites)

u_d type	Alg	Solution	Mean	Network	Max	Min	Des	Over	Under	STDEV	Total over $m+d$
Rural	r-s	Initial	0.3735	7.8443	2.3547	0.0000	1	3	17	0.6392	4.5144
		Optimised	0.5063	10.6327	1.3880	0.0000	3	7	11	0.4370	3.4483
	p-a	Initial	0.3617	7.5966	0.9940	0.0000	1	4	16	0.3225	6.9320
		Optimised	0.4548	9.5508	1.0562	0.1124	3	3	15	0.2416	0.9035
	s-p-d	Initial	0.382392767	8.030248117	1.543014866	0	2	4	15	0.4269	5.2289
		Optimised	0.429179764	9.012775051	0.685086938	0.1061	3	1	17	0.1521	0.9314
	s-p-r	Initial	0.3585	7.5287	2.3115	0.0000	1	4	16	0.5301	4.0458
		Optimised	0.4252	8.9286	0.7213	0.0409	3	2	16	0.1749	1.3359
Suburban	p-a	Initial	0.3887	44.3114	3.8322	0	5	18	91	0.5194	26.8334
		Optimised	0.3561	40.5996	1.1484	0	8	17	89	0.2786	14.2255
	r-s	Initial	0.4866	55.4729	9.9799	0	1	21	92	1.1370	49.3775
		Optimised	0.3654	41.6558	2.9381	0	6	17	91	0.4786	31.2646
	s-p-d	Initial	0.3759	42.8535	2.9568	0	5	17	92	0.5150	34.8733
		Optimised	0.3709	42.2823	1.0905	0	13	18	83	0.2821	19.1382
	s-p-r	Initial	0.3710	42.2960	2.0826	0	8	19	87	0.4432	46.1451
		Optimised	0.3607	41.1212	1.5991	0	16	14	84	0.3216	18.7101
Urban	r-s	Initial	0.4001	80.4267	4.4120	0	14	33	154	0.6492	80.3059
		Optimised	0.4976	100.0176	7.6333	0	14	34	153	1.0599	94.7131
	p-a	Initial	0.3793	76.2417	3.7418	0	10	38	153	0.4818	61.6948
		Optimised	0.3756	75.4910	2.0607	0	17	37	147	0.3795	51.5405
	s-p-d	Initial	0.4315	86.7234	6.4746	0	12	41	148	0.6656	63.8442
		Optimised	0.4316	86.7518	6.4746	0	11	41	149	0.6017	60.6634
	s-p-r	Initial	0.5508	110.7122	24.2050	0	8	38	155	1.7773	65.0424
		Optimised	0.4041	81.2151	2.2575	0	8	45	148	0.4100	57.6131

Table D.3: Uplink network statistics relating to optimisations performed on dimensioned network designs where each site is configured with a single omnidirectional antenna (uniformly distributed traffic and sites)

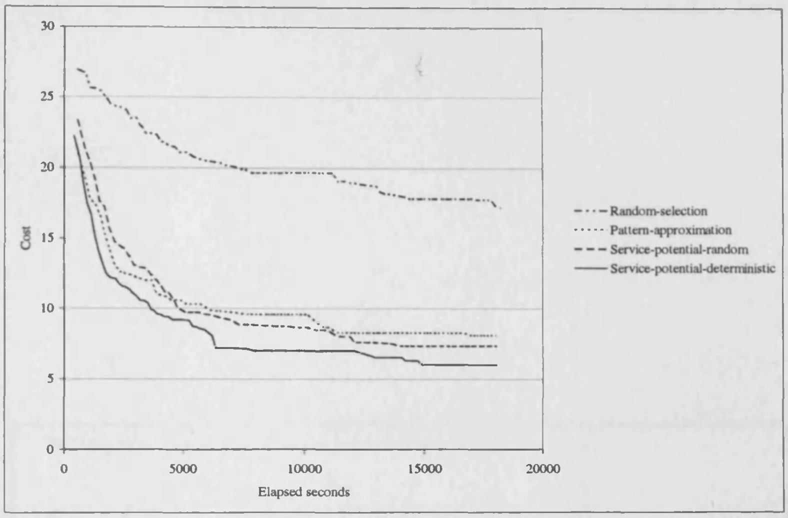


Figure D.1: Progress of optimisation for a rural scenario (uniformly distributed traffic and sites)

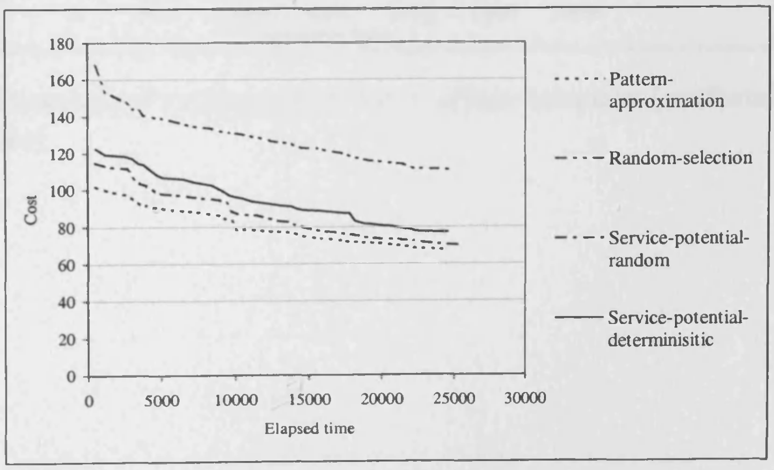


Figure D.2: Progress of optimisation for a suburban scenario (uniformly distributed traffic and sites)

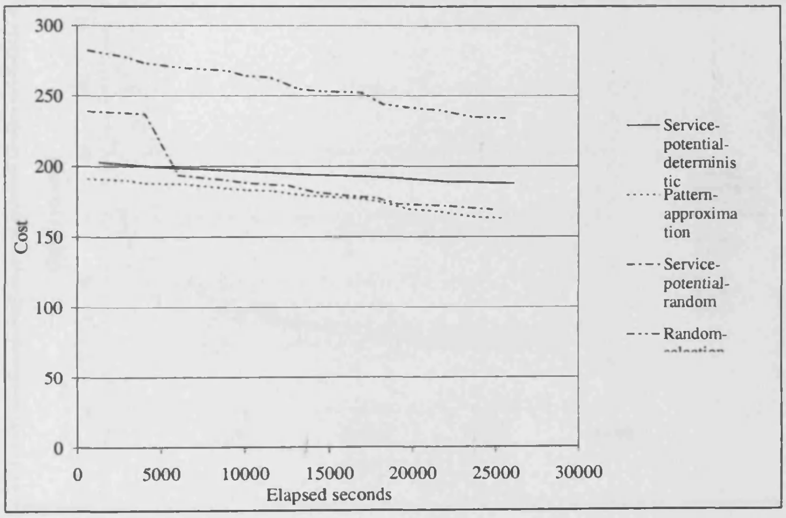


Figure D.3: Progress of optimisation for a urban scenario (uniformly distributed traffic and sites)

Optimisation results obtained when considering non-uniformly distributed traffic and sites are displayed in table D.4. Network statistics associated with these optimisation results can be found in table for the downlink D.5 and table D.6 for the uplink.

- a graph showing the progress of the optimisation for a rural scenario can be seen in figure D.4 (all sites have a single omnidirectional antenna);
- a graph showing the progress of the optimisation for a rural scenario can be seen in figure D.5 (all sites are sectorized).

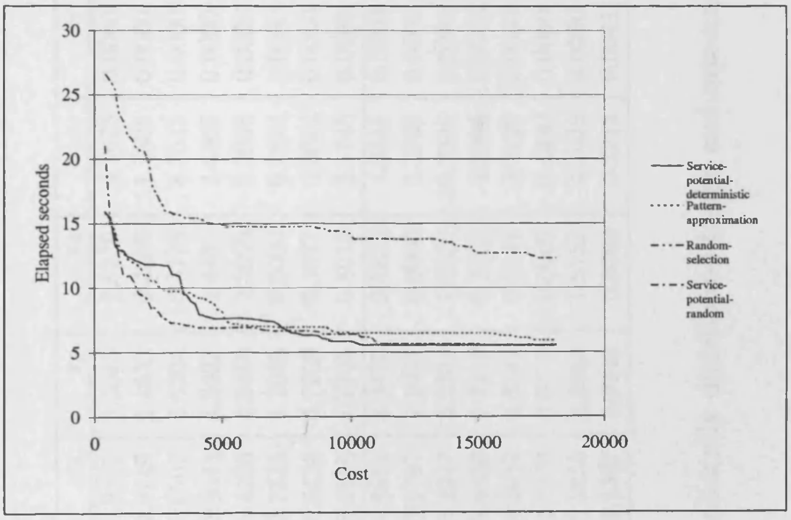


Figure D.4: Uniform traffic non-uniform sites (omnidirectional, rural)

A_k	Alg	Solution	e	e_4	e_5	e_6	e_7	e_2	e_3	e_8	e_9
Dir	p-a	Initial	30.9956	5.9311	5.0043	2.8239	9.7675	0.0000	0.0000	5.7569	1.7118
		Optimised	9.8210	2.9749	2.4633	0.4869	1.7808	0.0000	0.0000	1.1876	0.9275
	r-s	Initial	59.2457	7.0507	6.5304	16.3775	8.7515	0.0000	0.0000	6.3187	14.2168
		Optimised	17.2995	3.9544	4.3403	1.4481	4.4365	0.0000	0.0000	1.7665	1.3537
	s-p-d	Initial	22.0666	5.4205	4.5456	2.5095	5.2938	0.0000	0.0000	2.5403	1.7570
		Optimised	5.1483	2.7333	1.1618	0.0000	0.1874	0.0000	0.0000	0.5493	0.5165
	s-p-r	Initial	29.3617	5.6416	4.7209	5.1627	6.6072	0.0000	0.0000	3.1806	4.0487
		Optimised	10.6457	3.3865	1.7705	0.8015	2.1745	0.0000	0.0000	1.4089	1.1038
Omni	p-a	Initial	15.8772	4.8811	3.3470	0.5852	4.0615	0.0000	0.0000	2.1119	0.8905
		Optimised	5.9068	3.1797	1.1077	0.0000	0.3766	0.0000	0.0000	0.7697	0.4731
	r-s	Initial	26.5231	5.4927	4.9384	1.3539	10.2526	0.0000	0.0000	3.1245	1.3610
		Optimised	12.2980	2.6850	2.2219	0.3412	4.9398	0.0000	0.0000	1.3666	0.7436
	s-p-d	Initial	15.8228	4.5952	3.6341	0.6141	3.7122	0.0000	0.0012	2.2166	1.0493
		Optimised	5.5336	2.7273	0.9713	0.0000	0.4940	0.0000	0.0000	0.7591	0.5819
	s-p-r	Initial	20.9656	5.5255	4.2853	1.5157	4.1639	0.0000	0.0000	3.4528	2.0222
		Optimised	5.4880	3.1327	0.9445	0.0000	0.3213	0.0041	0.0043	0.5970	0.4842

Table D.4: Optimisation results (uniformly distributed traffic and non-uniformly distributed sites)

A_k	Alg	Solution	Mean	Network	Max	Min	Des	Over	Under	STDEV	Total over $m+d$	%STP	%MS
Dir	p-a	Initial	0.8011	16.8232	5.7569	0.0000	0	6	15	0.6516	9.7675	100	100
		Optimised	0.5616	11.7943	1.3104	0.1228	5	7	9	0.2433	1.7808	100	100
	r-s	Initial	0.6686	14.0411	6.3187	0.0000	0	4	17	3.1301	8.7515	100	100
		Optimised	0.5960	12.5161	1.7665	0.0000	0	9	12	0.3810	4.4365	100	100
	s-p-d	Initial	0.6184	12.9868	2.5403	0.0000	1	7	13	0.5247	5.2938	100	100
		Optimised	0.5457	11.4600	0.7775	0.2281	11	3	7	0.2044	0.1874	100	100
	s-p-r	Initial	0.6675	14.0168	3.1806	0.0000	2	5	14	0.9121	6.6072	100	100
		Optimised	0.6078	12.7628	1.4089	0.0000	9	5	7	0.3255	2.1745	100	100
Omni	p-a	Initial	0.6130	12.2608	2.1543	0.0424	1	6	13	0.3795	4.0615	100.0000	100.00
		Optimised	0.5632	11.2631	0.7932	0.0235	10	6	4	0.2118	0.3766	100.0000	100.00
	r-s	Initial	0.8511	17.0219	3.1245	0.0000	1	7	12	0.6316	10.2526	100.0000	100.00
		Optimised	0.7383	14.7663	1.4606	0.0940	2	9	9	0.3619	4.9398	100.0000	100.00
	s-p-d	Initial	0.5933	11.8668	2.2166	0.0000	2	7	11	0.3697	3.7122	100.0000	99.88
		Optimised	0.5842	11.6843	0.7980	0.0389	10	6	4	0.2385	0.4940	100.0000	100.00
	s-p-r	Initial	0.5719	11.4377	3.4528	0.0000	2	5	13	0.5015	4.1639	100.0000	100.00
		Optimised	0.5746	11.4921	0.7853	0.1883	6	7	7	0.2331	0.3213	99.5918	99.57

Table D.5: Downlink network statistics for a rural scenario (uniformly distributed traffic and non-uniform distributed sites)

A_k	Alg	Solution	Mean	Network	Max	Min	Des	Over	Under	STDEV	Total over $m + d$
Dir	p-a	Initial	0.4206	8.8329	1.7118	0	0	5	16	0.5221	9.7675
		Optimised	0.4391	9.2221	1.0767	0.1494	4	2	15	0.2084	1.7808
	r-s	Initial	1.0013	21.0268	14.2168	0	0	3	18	3.1114	8.7515
		Optimised	0.4474	9.3953	1.3537	0	2	4	15	0.3493	4.4365
	s-p-d	Initial	0.4301	9.0311	1.7570	0	2	4	15	0.4879	5.2938
		Optimised	0.4198	8.8157	0.5997	0.0832	8	0	13	0.1585	0.1874
	s-p-r	Initial	0.5461	11.4681	4.0487	0	1	5	15	0.9036	6.6072
		Optimised	0.4492	9.4325	1.1038	0	5	3	13	0.2820	2.1745
Omni	p-a	Initial	0.3547	7.0946	0.9115	0.0210	1	4	15	0.2716	4.0615
		Optimised	0.3896	7.7923	0.6297	0.1567	2	0	18	0.1147	0.3766
	r-s	Initial	0.3681	7.3622	1.3610	0.0000	1	5	14	0.3916	10.2526
		Optimised	0.4505	9.0100	0.8388	0.0952	4	3	13	0.2092	4.9398
	s-p-d	Initial	0.3674	7.3475	1.0493	0.0000	3	3	14	0.2880	3.7122
		Optimised	0.4154	8.3074	0.6437	0.0617	4	0	16	0.1639	0.4940
	s-p-r	Initial	0.3596	7.1917	2.0222	0.0000	3	2	15	0.4517	4.1639
		Optimised	0.3880	7.7591	0.6058	0.1217	2	0	18	0.1328	0.3213

Table D.6: Uplink network statistics for a rural scenario (uniformly distributed traffic and non-uniformly distributed sites)

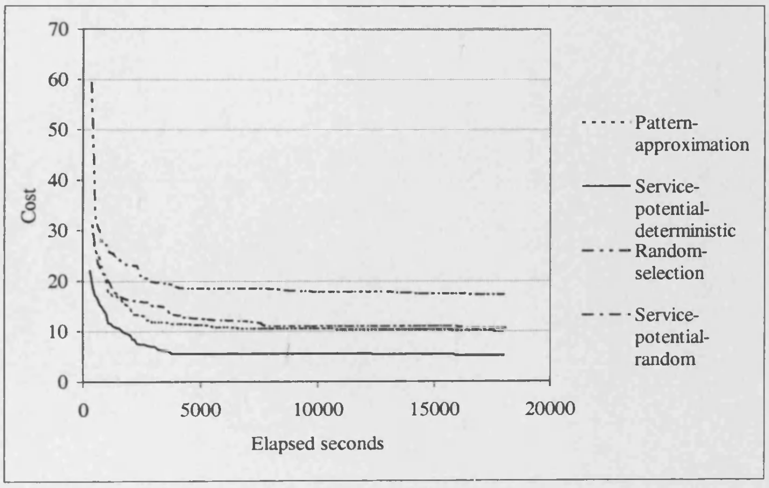


Figure D.5: Uniform traffic non-uniform sites (directional, rural)

Optimisation results for network designs where all the sites are sectorized considering non-uniformly distributed traffic are displayed in table D.7 and uniformly distributed sites. Network statistics associated with these optimisation results can be found in table for the downlink D.8 and table D.9 for the uplink.

u_d type	Alg	Solution	e	e_4	e_5	e_6	e_7	e_2	e_3	e_8	e_9
Rur	p-a	Initial	43.7630	8.2091	7.8439	4.7044	10.7808	0.0000	0.0000	8.2024	4.0225
		Optimised	26.7709	5.4694	6.0595	3.5248	5.7558	0.0000	0.0000	3.4593	2.5021
	r-s	Initial	45.6714	9.2489	9.0992	5.6697	8.8960	0.0000	0.0000	7.7005	5.0572
		Optimised	32.9872	6.7207	6.6031	5.3056	3.9024	0.0000	0.0000	4.5624	5.8930
	s-p-d	Initial	28.6367	6.4901	5.6331	3.9265	7.1492	0.0000	0.0000	3.2515	2.1864
		Optimised	8.9404	3.4963	1.7618	0.4061	1.5169	0.0000	0.0000	0.9094	0.8499
	s-p-r	Initial	30.7745	6.7221	5.6502	3.7996	7.3366	0.0000	0.0000	4.1249	3.1412
		Optimised	7.6419	2.8998	1.5317	0.4280	1.0257	0.0000	0.0000	0.8814	0.8753
Sub	p-a	Initial	175.7753	46.0365	43.3781	26.6533	41.2694	0.0065	0.0000	12.1715	6.2599
		Optimised	156.7077	42.5595	39.3950	24.8986	33.7112	0.0065	0.0001	9.2996	6.8371
	r-s	Initial	245.3846	48.9012	46.8543	37.9862	66.0723	0.0065	0.0001	26.8317	18.7324
		Optimised	211.3853	49.2874	46.5831	26.8555	42.4507	0.0065	0.0007	26.7095	19.4918
	s-p-d	Initial	151.3919	34.0675	29.7729	25.7387	44.5850	0.0139	0.0360	9.6990	7.4790
		Optimised	111.3529	33.5105	25.6366	12.8772	31.5889	0.0155	0.0254	4.6268	3.0721
	s-p-r	Initial	173.0729	34.4085	31.5677	24.3767	55.1787	0.0065	0.0000	18.3950	9.1397
	Optimised	122.9766	31.7751	29.4924	15.2054	35.4467	0.0114	0.0327	6.3688	4.6440	

Table D.7: Optimisation results (uniformly distributed sites and non-uniformly distributed traffic)

u_d type	Alg	Solution	Mean	Network	Max	Min	Des	Over	Under	STDEV	Total over $m+d$	%STP	%MS
Rur	r-s	Initial	0.5475	11.4968	7.7005	0	0	3	18	1.1650	8.8960	100	100
		Optimised	0.4181	8.7795	4.5624	0	2	1	18	1.2646	3.9024	100	100
	p-a	Initial	0.6970	14.6369	8.2024	0	0	3	18	0.9935	10.7808	100	100
		Optimised	0.5484	11.5163	3.4593	0	0	4	17	0.6911	5.7558	100	100
	s-p-d	Initial	0.6470	13.5875	3.2515	0	1	6	14	0.6695	7.1492	100	100
		Optimised	0.5818	12.2170	1.0831	0.1737	5	7	9	0.2855	1.5169	100	100
	s-p-r	Initial	0.6565	13.7875	4.1249	0	1	6	14	0.7946	7.3366	100	100
		Optimised	0.5791	12.1607	1.0105	0.129	8	6	7	0.2468	1.0257	100	100
Sub	p-a	Initial	0.5347	60.9578	12.1715	0	2	12	100	1.0644	41.2694	99.3469	99.9964
		Optimised	0.5027	57.3128	9.2996	0	2	11	101	1.0782	33.7112	99.3469	99.9909
	r-s	Initial	0.7243	82.5729	26.8317	0	2	13	99	2.2184	66.0723	99.3469	99.9928
		Optimised	0.5166	58.8939	26.7095	0	1	12	101	1.8731	42.4507	99.3469	99.9312
	s-p-d	Initial	0.7052	80.3971	9.6990	0	6	30	78	0.9722	44.5850	98.6122	96.4020
		Optimised	0.6296	71.7740	4.6268	0	10	30	74	0.6003	31.5889	98.4490	97.4559
	s-p-r	Initial	0.7872	89.7438	18.3950	0	4	37	73	1.0990	55.1787	99.3469	99.9982
		Optimised	0.6292	71.7294	6.3688	0	7	33	74	0.7024	35.4467	98.8571	96.7261

Table D.8: Downlink network statistics for uniformly distributed sites and non-uniformly distributed traffic (directional)

u_d type	Alg	Solution	Mean	Network	Max	Min	Des	Over	Under	STDEV	Total over $m + d$
Rur	p-a	Initial	0.3892	8.1738	4.0225	0.0000	1	2	18	0.9421	10.7808
		Optimised	0.4693	9.8557	2.5021	0.0000	5	2	14	0.6863	5.7558
	r-s	Initial	0.3810	8.0007	5.0572	0.0000	0	2	19	1.1525	8.8960
		Optimised	0.4935	10.3640	5.8930	0.0000	3	2	16	1.2623	3.9024
	s-p-d	Initial	0.4500	9.4502	2.1864	0.0000	2	4	15	0.6384	7.1492
		Optimised	0.4238	8.9004	0.8889	0.0391	3	4	14	0.2352	1.5169
	s-p-r	Initial	0.4186	8.7915	3.1412	0.0000	1	3	17	0.7563	7.3366
		0.4446	Optimised	9.3374	1.0033	0.1279	4	2	15	0.2048	1.0257
Sub	p-a	Initial	0.3828	43.6405	6.2599	0	1	12	101	1.0535	41.2694
		Optimised	0.3984	45.4220	6.8371	0	4	11	99	1.0731	33.7112
	s-p-r	Initial	0.4763	54.2930	9.1397	0	5	22	87	1.0537	55.1787
		Optimised	0.4200	47.8754	4.6440	0	11	19	84	0.6703	35.4467
	s-p-d	Initial	0.4906	55.9281	7.4790	0	7	20	87	0.9480	44.5850
		Optimised	0.3788	43.1866	3.0721	0	7	15	92	0.5449	31.5889
	r-s	Initial	0.4546	51.8281	18.7324	0	2	9	103	2.2018	66.0723
		Optimised	0.3526	40.1912	19.4918	0	2	8	104	1.8658	42.4507

Table D.9: Uplink network statistics for uniformly distributed sites and non-uniformly distributed traffic (directional)

Optimisation results for network designs where all sites are sectorized and considering non-uniformly distributed traffic are displayed in table D.10 and uniformly distributed sites. Network statistics associated with these optimisation results can be found in table for the downlink D.11 and table D.12 for the uplink.

$u_d$type	Alg	Solution	e	e_4	e_5	e_6	e_7	e_2	e_3	e_8	e_9
Rur	p-a	Initial	36.4963	0	0	4.6954	4.4471	8.5991	8.2923	5.3554	5.1071
		Optimised	26.1345	0	0.0016	3.4092	3.9888	6.4655	4.6066	3.8374	3.8255
	r-s	Initial	40.1865	0	0	7.9047	4.4999	8.3153	8.4838	5.8228	5.1599
		Optimised	32.2704	0	0.0033	4.9642	4.1576	7.1573	5.6641	5.5926	4.7314
	s-p-d	Initial	30.7716	0	0	3.819	8.4667	5.387	4.9235	3.1734	5.002
		Optimised	9.0532	0	0.0001	0.4431	2.8063	2.3266	1.1038	0.8728	1.5006
	s-p-r	Initial	53.0256	0	0	19.495	8.8872	6.1383	6.0172	9.4465	3.0414
		Optimised	9.9727	0	0	0.943	2.0641	2.6885	1.8557	1.0862	1.3351
Sub	p-a	Initial	238.6402	49.1606	48.9915	31.2423	66.6866	0.0000	0.0014	28.3621	14.1956
		Optimised	188.6805	48.0460	48.2883	28.5837	41.8664	0.0000	0.0014	12.5072	9.3875
	r-s	Initial	241.8647	50.3657	50.6012	41.5833	60.0628	0.0000	0.0037	23.5117	15.7362
		Optimised	214.3670	50.7600	50.3714	33.5905	42.6742	0.0000	0.0041	20.4876	16.4792
	s-p-d	Initial	208.9708	43.7098	43.1921	40.1234	57.7439	0.0000	0.0065	14.8920	9.3031
		Optimised	171.7438	41.8435	41.4806	27.6946	38.4737	0.0000	0.0083	12.6796	9.5635
	s-p-r	Initial	235.9198	41.4604	41.7930	49.6060	73.7372	0.0008	0.0057	17.3649	11.9517
		Optimised	159.9486	41.4257	40.6604	23.8699	35.8825	0.0000	0.0116	10.3512	7.7474

Table D.10: Optimisation results for omnidirectional (Uniform sites and non-uniform traffic)

u_d	Alg	Solution	Mean	Network	Max	Min	Des	Over	Under	STDEV	Total over $m+d$	%STP	%MS
Rur	p-a	Initial	0.3537	7.0748	5.1071	0	0	1	19	1.1803	4.4471	100	100
		Optimised	0.5331	10.6622	3.8366	0.0111	0	4	16	0.855	3.9888	100	100
	r-s	Initial	0.3483	6.9669	5.1599	0	1	1	18	1.4432	4.4999	100	100
		Optimised	0.4767	9.5335	4.7314	0	0	2	18	1.2298	4.1576	100	100
	s-p-d	Initial	0.7532	15.063	5.002	0	1	5	14	0.8012	8.4667	100	100
		Optimised	0.6755	13.5101	1.6128	0.1122	2	8	10	0.3009	2.8063	100	100
	s-p-r	Initial	0.7135	14.2701	3.0414	0	0	5	15	2.7584	8.8872	100	100
		Optimised	0.5980	11.9607	1.4951	0.16	6	5	9	0.2979	2.0641	100	100
Sub	p-a	Initial	0.7233	75.2257	28.3621	0	1	11	92	1.8059	66.6866	100.00	99.86
		Optimised	0.4924	51.2116	12.5072	0	1	12	91	1.5428	41.8664	100.00	99.86
	r-s	Initial	0.6414	66.7016	23.5117	0	0	9	95	2.2771	60.0628	100.00	99.63
		Optimised	0.4741	49.3028	20.4876	0	0	7	97	2.1003	42.6742	100.00	99.50
	s-p-d	Initial	0.7010	72.9072	14.8920	0	1	18	85	1.4941	57.7439	100.00	99.35
		Optimised	0.5334	55.4784	12.6796	0	1	19	84	1.2083	38.4737	100.00	99.17
	s-p-r	Initial	0.8692	90.3932	17.3649	0	2	18	84	1.8392	73.7372	99.92	99.43
		Optimised	0.5190	53.9802	10.3512	0	3	20	81	1.0997	35.8825	100.00	98.84

Table D.11: Downlink network statistics for uniformly distributed sites and non-uniformly distributed traffic (omnidirectional)

u_d	Alg	Solution	Mean	Network	Max	Min	Des	Over	Under	STDEV	Total over $m+d$
Rur	p-a	Initial	0.3508	7.0162	5.3554	0	0	1	19	1.1803	4.4471
		Optimised	0.4013	8.0251	3.8494	0.012	2	2	16	0.8442	3.9888
	r-s	Initial	0.5375	10.7494	5.8228	0	0	3	17	1.4301	4.4999
		Optimised	0.4456	8.9126	5.5926	0	2	2	16	1.2294	4.1576
	s-p-d	Initial	0.489	9.7802	3.1734	0	1	4	15	0.754	8.4667
		Optimised	0.4837	9.6745	0.9809	0.1081	6	4	10	0.2277	2.8063
	s-p-r	Initial	1.2438	24.8767	9.4465	0	0	6	14	2.7042	8.8872
		Optimised	0.4796	9.5912	1.184	0.0979	4	3	13	0.272	2.0641
Sub	p-a	Initial	0.3800	39.5152	14.1956	0	1	10	93	1.7726	66.6866
		Optimised	0.3643	37.8837	9.3875	0	2	9	93	1.5374	41.8664
	r-s	Initial	0.4640	48.2608	15.7362	0	1	7	96	2.2701	60.0628
		Optimised	0.3826	39.7883	16.4792	0	3	5	96	2.0983	42.6742
	s-p-d	Initial	0.5230	54.3923	9.3031	0	1	15	88	1.4834	57.7439
		Optimised	0.4247	44.1711	9.5635	0	0	18	86	1.2033	38.4737
	s-p-r	Initial	0.6374	66.2945	11.9517	0	2	16	86	1.8244	73.7372
		Optimised	0.3930	40.8757	7.7474	0	1	18	85	1.0924	35.8825

Table D.12: Uplink network statistics for uniformly distributed sites and non-uniformly distributed traffic (omnidirectional)