Approaches for the classification of traffic and radio resource management in mobile cellular networks: an application to South Africa

Anish Mathew Kurien

ÉCOLE DOCTORALE
«Mathématiques, Sciences et Techniques de l'Information et de la Communication»

Thèse de doctorat

Spécialité : Informatique

Anish Mathew Kurien

Approches pour la classification du trafic et l'optimisation des ressources radio dans les réseaux cellulaires : Application à l'Afrique du Sud

Mai 2012

COMPOSITION DU JURY

Yacine AMIRAT	Université Paris-Est, Créteil, France	Président
Jalel BEN-OTHMAN	Université Paris-13, France	Rapporteur
Willem CLARK	Université à Johannesburg, Afrique Du Sud	Rapporteur
Prosper CHEMOUIL	Orange, France Telecom, France	Examinateur
Yskandar HAMAM	F'SATI, Pretoria, Afrique Du Sud	Co-Directeur de Thèse
Barend J VAN WYK	TUT, Pretoria, Afrique Du Sud	Co-Directeur de Thèse
Abdelhamid MELLOUK	Université Paris-Est, Créteil VDM, (UPEC), France.	Directeur de Thèse

Abstract

The growth in the number of cellular mobile subscribers worldwide has far outpaced expected rates of growth with worldwide mobile subscriptions reaching 6 Billion subscribers in 2011 according to the International Telecommunication Union (ITU). More than 75% of this figure is in developing countries. With this rate of growth, greater pressure is placed on radio resources in mobile networks which impacts on the quality and grade of service (GOS) in the network. With varying demands that are generated from different subscriber classes in a network, the ability to distinguish between subscriber types in a network is vital to optimise infrastructure and resources in a mobile network. In this study, a new approach for subscriber classification in mobile cellular networks is proposed. In the proposed approach, traffic data extracted from two network providers in South Africa is considered. The traffic data is first decomposed using traditional feature extraction approaches such as the Empirical Mode Decomposition (EMD) and the Discrete Wavelet Packet Transform (DWPT). The results are then compared with the Difference Histogram approach which considers the number of segments of increase in the time series. Based on the features extracted, classification is then achieved by making use of a Fuzzy C-means algorithm. It is shown from the results obtained that a clear separation between subscriber classes based on inputted traffic signals is possible through the proposed approach. Further, based on the subscriber classes extracted, a novel two-level hybrid channel allocation approach is proposed that makes use of a Mixed Integer Linear Programming (MILP) model to consider the optimisation of radio resources in a mobile network. In the proposed model, two levels of channel allocation are considered: the first considers defining a fixed threshold of channels allocated to each cell in the network. The second level considers a dynamic channel allocation model to account for

the variations in traffic experienced in each traffic class identified. Using the optimisation solver, CPLEX, it is shown that an optimal solution can be achieved with the proposed two-level hybrid allocation model.

Résumé

Selon l'Union Internationale des Télécommunications (UIT), la progression importante du nombre de téléphones mobiles à travers le monde a dépassé toutes les prévisions avec un nombre d'utilisateurs estimé à 6 Mds en 2011 dont plus de 75% dans les pays développés. Cette progression importante produit une pression forte sur les opérateurs de téléphonie mobile concernant les ressources radio et leur impact sur la qualité et le degré de service (GoS) dans le réseau. Avec des demandes differenciées de services émanant de différentes classes d'utilisateurs, la capacité d'identifier les types d'utilisateurs dans le réseau devient donc vitale pour l'optimisation de l'infrastructure et des ressources. Dans la présente thése, une nouvelle approche de classification des utilisateurs d'un réseau cellulaire mobile est proposée, en exploitant les données du trafic réseau fournies par deux opérateurs de téléphonie mobile en Afrique du Sud. Dans une première étape, celles-ci sont décomposées en utilisant deux méthodes multi-échelles; l'approche de décomposition en mode empirique (Empirical Mode Decomposition approach (EMD)) et l'approche en Ondelettes Discrètes (Discrete Wavelet Packet Transform approach (DWPT)). Les résultats sont ensuite comparés avec l'approche dite de Difference Histogram qui considère le nombre de segments de données croissants dans les séries temporelles. L'approche floue de classification Fuzzy C-means(FCM) est utilisée par la suite pour déterminer les clusters, ou les différentes classes présentes dans les données, obtenus par analyse multi-échelles et par différence d' histogrammes. Les résultats obtenus montrent, pour la méthode proposée, une séparation claire entre les différentes classes de trafic par rapport aux autres méthodes. La deuxième partie de la thèse concerne la proposition d'une approche d'optimisation des ressources réseau, qui prend en compte la variation de la demande en termes de trafic base sur les classes d'abonnés précédemment

identifiés dans la première partie. Une nouvelle approche hybride en deux niveaux pour l'allocation des canaux est proposée. Le premier niveau considre un seuil fixe de canaux alloués à chaque cellule en prenant en considération la classe d'abonnés identifiée par une stratégie statique d'allocation de ressources tandis que le deuxième niveau considère une stratégie dynamique d'allocation de ressources. Le problème d'allocation de ressources est formulé comme un problème de programmation linéaire mixte (Mixed-Integer Linear programming (MILP)). Ainsi, une approche d'allocation par période est proposée dans laquelle un groupe de canaux est alloué de façon dynamique pour répondre à la variation de la demande dans le réseau. Pour résoudre le problème précédent, nous avons utilisé l'outil CPLEX. Les résultats obtenus montrent qu'une solution optimale peux être atteinte par l'approche proposée (MILP).

Dedication

It is in Him that we live, move, and have our very being... To Him be all the Glory, Honor and Praise...

This work is dedicated to my loving family: My parents Mr & Mrs Kurien and my in-laws, Mr & Mrs Mathew. To my wife, Deepa and children, Abel and Caleb.

To Jilu, Anita, Joel, Josh, and Alissa, Aju, Elizabeth, Ashish, Ranjana, Yohan, Josef, Joe, Vineeth, and Daniel, for all your prayers and sacrifices.

May our Gracious Lord continue to bless each and every one of you abundantly.

Acknowledgements

This work would not be possible without the encouragement and support of various people. Firstly, I would like to acknowledge my supervisors, Prof. Barend J Van Wyk, Prof. Yskandar Hamam both from F'SATI/TUT and Prof. Abdelhamid Mellouk from the LISSI laboratory, Université Paris-Est, Cretéil VDM for all your contributions, suggestions for improvement, and your guidance during this study.

I would like to extend a special word of gratitude to Dr. G Noël and Prof. K Djouani, for all the endless number of hours and support. This work would not been possible without your valuable advice and input. I would also like to thank Dr. D Chatelain and Prof. L Snyman who were instrumental during the start of this work. I would like to acknowledge Prof. F Rocaries, Director of F'SATI for all the support from F'SATI. To all my colleagues at F'SATI and the Department of Electrical Engineering, thank you for all your support. I would like to also extend a special word of thanks to Prof. Adisa Jimoh, Head of Department of Electrical Engineering, for his support and advice. I would also like to thank Dr. Jaco Jordan for his contributions on the Semi-Parametric Decomposition approach that was considered as an alternative signal decomposition approach for the traffic class classification. I would also like to extend a special word of thanks to Mr. M Drewes and Mr. C De Wet for input regarding data used in this study. I would like to thank the following for financial assistance during this study: the Telkom Centre of Excellence programme, the National Research Foundation, Tshwane University of Technology, and the French Embassy.

Finally, to the Life Spring Ministries, for all the prayers and support, may God Bless you abundantly.

Declaration

I hereby declare that the dissertation submitted for the degree of D Tech: Engineering: Electrical, at Tshwane University of Technology, Pretoria, South Africa and the PhD at Université Paris-Est, Créteil, Paris, France is my own original work and has not previously been submitted to any other institution of higher education. I further declare that all sources cited or quoted are indicated and acknowledged by means of a comprehensive list of references.

Anish Mathew Kurien, May 2012.

Contents

List of Figures

List of Tables

Glossary

2G 2nd Generation. 72, 97

3G 3rd Generation. 23, 72, 97

ANN Artificial Neural Network. 19

BCA Borrowing Channel Algorithm. 24

BSC Base Station Controller. 113

BTS Base Station Site. 8, 20, 23, 26, 72, 80, 85, 92, 95, 97, 112, 123

CAP Capacity Allocation Problem. 6, 8, 24, 25, 29

CBD Central Business District. 43, 53, 54, 58, 59, 61, 62, 68, 69

CDMA Code Division Multiple Access. 23

CDR Call Data Records. 17

CFLP Capacitated Facility Location Problem. 80

COP Combinatory Optimisation Problem. 26, 71

DCA Dynamic Channel Allocation. 24, 26, 29, 116

DFT Discrete Fourier Transform. 35

DH Difference Histogram. 11, 20, 62

DWPT Discrete Wavelet Packet Transform. 11, 19, 38, 46, 49, 51, 54, 59, 64, 95

DWT Discrete Wavelet Transform. 19, 35, 37, 38

EMD Empirical Mode Decomposition. 11, 18, 20, 34, 36, 50, 51, 58, 95

FCA Fixed Channel Allocation. 29

FCM Fuzzy C-Means. 50, 51, 58

FDD Frequency Division Duplex. 113

FR Full Rate. 113

GA Genetic Algorithm. 22, 23

GDP Gross Domestic Product. 3

GOS Grade of Service. 5, 12, 13, 68

GSM Global System for Mobile Communications. 18, 63, 112

HCA Hybrid Channel Allocation. 25, 26, 118

HR Half Rate. 113

ILP Integer Linear Programming. 25, 73–75, 77, 79

IMF Intrinsic Mode Functions. 20, 34, 53

ITU International Telecommunication Union. 1

LP Linear Programming. 77, 79, 84

MILP Mixed-Integer Linear Programming. 10, 11, 25, 27, 28, 73, 75, 76, 84, 87–89, 92, 93, 97

MIP Mixed-Integer Programming. 27

MPS Mathematical Programming System. 84

MS Mobile Station. 112

MSC Mobile Switching Centre. 113

NSS Network Subsystem. 112

OMC Operational Maintenance Centre. 6, 8, 18, 30, 34, 42, 64

OPEX Operational Expenditure. 68

PCA Principal Component Analysis. 48, 64

RF Radio Frequency. 5

SINR Signal to Interference Noise Ratio. 112, 123, 124

SUB Sub-urban. 43, 53, 58, 61, 62, 68, 70

SVM State Vector Machine. 19

TCH Traffic Channel. 6, 18, 42

TDMA Time Division Multiple Access. 113

TWN Township. 43, 53, 58, 61–63

UMTS Universal Mobile Telecommunication System. 27

UniFL Universal Facility Location Problem. 75

WMAT Wavelet-based Multi-Resolution Analysis Technique. 6, 18, 50

WPT Wavelet Packet Transform. 19

Chapter 1

Introduction

1.1 Introduction

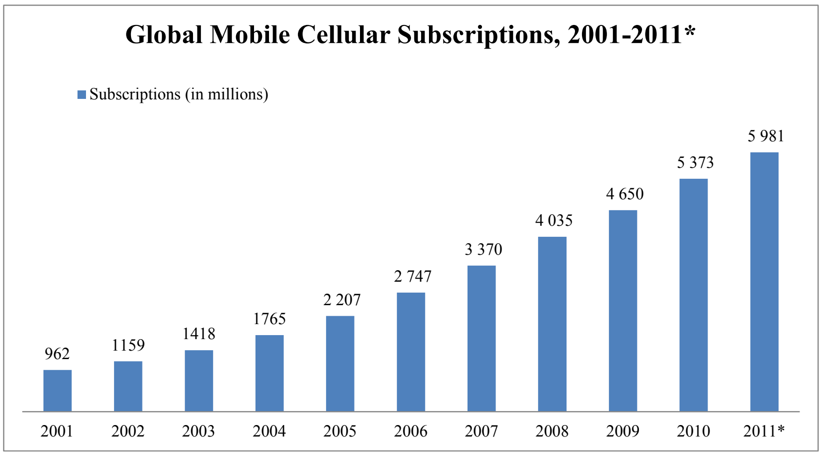
This chapter provides the background to the study and highlights the motivation for the study. The problems considered in the study are highlighted followed by research methodology employed for the study, main contributions of the study, and ends with an overview of the chapters in the thesis.

1.2 Background

When Marconi first conducted experiments on the first wireless communications systems, few would have thought at the time that mobile cellular technologies would grow to become one of the most adopted technologies worldwide. According to the International Telecommunication Union ITU, mobile cellular technologies have become the most popular and widespread personal technologies on the planet with an estimated 6 Billion subscribers globally by the end of 2011. It was estimated that by the end of 2010, 90% of the world's population and 80% of rural population had access to mobile networks [51]. According to the ITU, the mobile penetration rate for developing countries was at a level that Sweden (the 2008 benchmark for mobile phones penetration) had reached 9.4 earlier highlighting that developing countries were only 10 years behind the benchmark in 2008 [50]. Considering the African market, one of the greatest success stories has been the growth of mobile telephony across the continent. In 2007, the growth of the mobile market was seen to be the largest of any region growing at a rate of nearly twice that of the global market [48] and has been seen as a significant contributor to the expansion of access to communication services to the majority of the population.

1.2.1 The Global Growth of the Mobile Cellular Market

According to the ITU, the global mobile subscriptions per 100 inhabitants in 2001 was 15.5. This figure grew to 86.7 in 2011. Figure 1.1 below illustrates the rate of growth in mobile subscriber subscriptions globally between 2001 and 2011.



* Estimate
Source: ITU World Telecommunication/ICT indicator database

Figure 1.1: Global Mobile Cellular Subscribers, 2001-2011

Though the rate of growth of mobile subscribers has been high, the penetration rates in Africa are still much lower when compared to the world average. This is illustrated in the Figure 1.2 [49].

1.2.2 Drivers for Mobile Subscriber Growth

The slow rate of growth in fixed line access in Africa has been a primary contributor to the rate of growth of mobile subscribers across Africa. However, various other factors have also contributed to the success in the rate of growth including:

1. Reduced Rollout Costs - Mobile cellular technologies have the benefit of being able to cover greater areas at reduced costs and with greater ease. With the

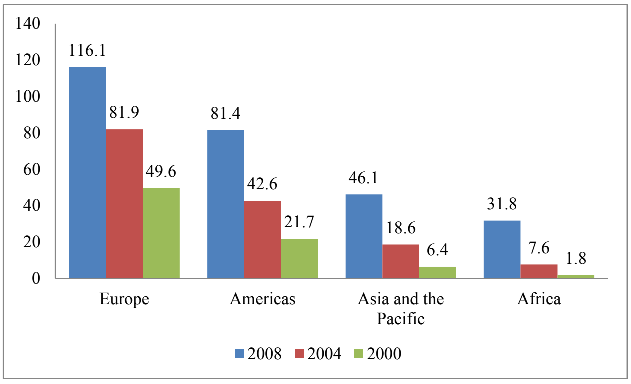


Figure 1.2: Mobile Cellular Penetration Rates: 2000-2008 [49]

challenge of reaching many rural communities, the ease of rolling out wireless access to many rural communities has been more viable and cost effective.

2. Innovative Business Models - Innovative business models have made mobile cellular services more accessible to the broader population, this inspite of the fact that Africa accounted for only over 2% of the world's Gross Domestic Product GDP in 2006 [52]. Low subscription prices, pre-paid services and low re-charge costs have added to the boom in mobile subscriber numbers in Africa. The introduction of roaming and cross-border roaming [52] has made wireless services more attractive and accessible.

3. Regulation - The liberalisation of regulation policies have fuelled competition across the African region. Many countries have opened their markets to foreign investment raising competition in these markets and making subscription rates more attractive for subscribers [52].

1.2.3 Traditional Radio Network Planning

With the growth in mobile subscribers experienced globally, and especially in Africa and in many developing countries, greater pressure is placed on mobile network providers to ensure that their networks continue to be competitive and that their network infrastructure is able to adapt to the increase in demand for services. The traditional approach to planning cellular networks has primarily focused on developing networks from an analytical approach where focus is given to radio propagation and interference analysis [106]. In the traditional approach of network planning, the objective is to obtain a network design that has been optimised to provide the best coverage and capacity for an area under consideration. Priority is given to providing optimum coverage in areas being planned for and capacity related issues are addressed in later parts of the planning process. Coverage planning considers the number of sites that are required to cover the geographical area under consideration while Capacity planning takes into account the amount of traffic that needs to be supported within the considered geographical area based on the number of users (subscribers) in the given area. The steps that are involved in the traditional planning approach is shown in Figure 1.3 [104].

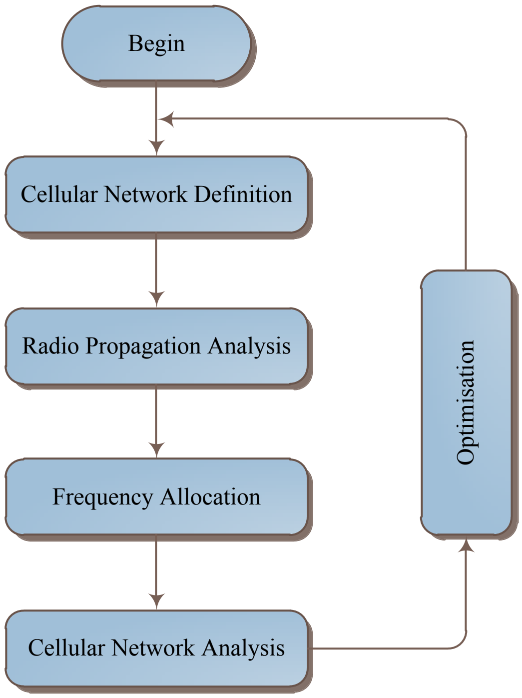


Figure 1.3: Traditonal Cellular Network Planning Process

Due to the radical and rapid usage of wireless networks, the primary objective of radio frequency RF coverage has to incorporate new design criteria to meet the greater demands based on the growth of cellular networks [104]. Network design criteria have to continuously consider factors that impact on the quality of the network, the Grade of Service GOS expectations, and the reduction in the costs of deployment to ensure that effective Average Return per User (ARPUs) are achieved by cellular network providers. Due to the constant growth in demand for capacity in the network, a systematic approach to cellular network planning is crucial to maintain effective growth and returns on investments [105].

1.2.4 Subscriber Segmentation and Time Series Data in Mobile Networks

One of the drawbacks of commonly used network planning methods is their inability to address the economical aspects of system deployment [107] and the neglect of factors such as user behaviour and demand distribution. With most environments today that have varying factors that influence traffic distributions in a network, the ability of the network planning solution to accurately detect traffic trends as well as traffic anomalies would be beneficial for effective capacity planning in networks. With the explosion of the information age, the growth and the access to information across all disciplines of industry has been exponential. The explosive growth in many databases has far outpaced the ability to interpret and digest this data [116]. Various kinds of data are generated in a typical telecommunication network. It is often useful to profile customers based on their patterns of phone usage. Information about a customer provides the opportunity to expand as well as increase profitability into specific markets [18]. A common method for segmentation is the use of Clustering techniques. Cluster algorithms can be employed to discover groups of customers with common attributes [113]. They are appropriate when very little information is known about the categorisation structure of the underlying data [104]. By grouping customers into selected clusters, different strategies may be employed for each cluster for effective and efficient service offerings targeted at an identified cluster or segment [113].

Time series data accounts for a significant amount of information stored in various disciplines such as business, medical, engineering, social sciences etc [59]. A time series can be considered to be a sequence of (real) numeric values in which a total order based on time stamps is defined. Time series are generally used to represent the temporal evolution of objects [36]. The Operations and Maintenance Centre OMC within a typical cellular network provides various measurements that are generated by different counters and provide information regarding traffic load [60]. Traffic load in the network can be measured from these counters which provide information on when each available Traffic Channel TCH is busy.

The traffic data extracted from the OMC represents a time varying signal which could contain vital information regarding subscriber behaviour. However, the non-linear nature of the traffic signals caused by the non-uniform nature of subscriber usage of mobile phones poses a challenge in the extraction of meaningful information from the signals. The use of signal processing approaches has been widely used for feature extraction and classification. However, one of the problems with traditional signal processing approaches is their inefficiency in providing sufficient information in the time domain. Multi-resolution techniques such as the wavelet transform provides the ability to handle signals in short time intervals for high frequency components and long time intervals for low frequency components [108]. Wavelet based multi-resolution analysis technique WMAT approaches have also shown to be useful in denoising multi-dimensional spatial/temporal signals containing steady/unsteady noise [42].

1.3 Problem Statement

A large number of repositories of time series data are generated on a daily basis within the OMC in a typical mobile network operator which store valuable information regarding subscriber behaviour. However, the feature extraction from the time series data is non-trivial due to the non-linear nature of the data due to the non-uniform behaviour of subscribers in the network. The primary objective of the study is to propose a suitable feature extraction and classification approach that is capable of adapting to the non-linear nature and the noise contained in the time series data. The end goal of subscriber classification in this study is to utilise the subscriber information extracted for a new radio resource optimisation model that focuses on the Channel Allocation Problem CAP. Although there they have been various models proposed in literature for solving of the CAP problem, the utilisation of subscriber related information in the CAP has not been directly considered.

1.3.1 Sub-Problems

The above problem can be divided into the following sub-problems:

1.3.1.1 Sub-Problem 1

Due to the non-linear nature of the time-series traffic data considered in this study, the first sub-problem is to propose a suitable feature extraction approach for the time series data obtained from a mobile cellular network operator. Depending on the approach considered, a suitable signal decomposition and feature extraction approach needs to be considered. Based on the features extracted, a classification approach suited to subscriber classification in mobile networks needs to be defined that takes into account the features extracted. The classification approach needs to ensure that minimal overlap exists between the identified traffic classes.

1.3.1.2 Sub-Problem 2

The second sub-problem considers the proposal of a new channel allocation approach that takes into account the traffic behaviour of the traffic classes identified. The proposed approach needs to consider two aspects of the behaviour traffic within identified traffic classes: (i) The consideration of a fixed channel allocation to cater for minimum traffic demand experienced in each traffic class. (ii) The formulation of a dynamic multiple period based channel allocation model that takes into account the irregular traffic variations experienced in the traffic classes identified.

1.4 Benefits of Study

The primary benefit of the study is three-fold.

1. Through the study, an effective feature extraction strategy suited to time series data extracted from mobile networks is defined. Three different approaches are considered. The ability of the three approaches to adapt to the non-linear nature of the time series data is shown.

2. Based on the above approach, a subscriber classification approach based on the features extracted is defined. The strategy provides a simple mechanism for determining subscriber types by applying the approach to any time series traffic data extracted from a mobile network and allows the planner to determine the type of subscriber characteristics inherent in the traffic data. Through this approach, the network planner is able to judge the traffic class that the data may belong to. This has the potential of helping a network planner to better judge the implications of the traffic class on the capacity demand requirements for the determined traffic class.

3. To enforce the benefit of conducting traffic class identification using the above approach, the final benefit of the study is the utilisation of the extracted traffic classes in the formulation of novel channel allocation approach referred to as a two-level hybrid channel allocation approach. The uniqueness of the approach is the consideration of a traditional hybrid channel allocation approaches as a first level channel optimisation based on peak demand identified per traffic class. A second level channel optimisation is conducted using a time-interval based allocation of resources using a mixed-integer linear programming which ensures that a global optimal solution for the CAP is obtained. It is shown that an optimal solution that considers the base station site BTS placement problem while ensuring capacity constraints of the channel allocation problem CAP can be achieved. The proposed model serves as an added contribution of this work.

1.5 Delimitations

While the study considers time series data extracted from the OMC in a mobile network,only daily traffic carried per cell is considered in this study. The study only considers voice traffic as this is the primary traffic carried on mobile networks in most developing countries. However, the approach can be applied to other types of network traffic classes. The proposed approach is also validated from a theoretical point of view and is not implemented on a live network.

1.6 Confidentiality

Due to the confidential nature of the data used in this study, the exact information of cell sites, areas considered, and network operator details will not be presented. For the purposes of demonstrating the approach, some information will be provided to highlight the benefits of the proposed approach in this study.

1.7 Research Methodology

The selected research methodology in this study will be experimental in nature. An overview of the different phases that were followed in the study are listed below.

1. Phase 1 - The first phase of the study would be to establish a robust feature extraction approach suitable for extracting useful features in the mobile network traffic data.

2. Phase 2 - The second phase defines a Subscriber Classification Approach that is based on the selected feature extraction approach that can be utilised for the resource allocation approach proposed in this study.

3. Phase 3 - The third phase of the study utilises the defined subscriber classes for the proposed resource allocation approach. An optimisation approach is selected based on the characteristics of the optimisation problem and validated to determine the benefits of the proposed approach.

Based on the results obtained from the proposed resource allocation scheme, the benefits of the approach on resource allocation in mobile networks will be highlighted.

1.8 Contributions and Outputs of Study

The main contributions of this study may be considered as follows:

1. A new approach for feature extraction and classification of traffic classes in mobile cellular networks is proposed in this study. The proposed approach makes use of existing signal decomposition, feature extraction, and classification methods. The benefit of the approach is in the application of the methods in conducting

subscriber classification in mobile networks. The selection of methods suited to the nature of the traffic signals considered is highlighted.

2. A varied approach to the difference histogram approach proposed in [109] is also shown in this study. The original algorithm considers feature extraction in time series data through the measurement of segments of increase in the time series data. The proposed variation in this study is to consider measuring the lengths of the segments as features extracted. This variation is shown to perform better for the data considered in this study.

3. A final contribution of this study is the proposal of a novel approach to channel allocation in mobile networks that makes use of a mixed-integer linear programming MILP approach for the allocation of radio resources to different traffic classes identified in the previous stage. The novelty of the approach is in the use of a two-level approach that considers a hybrid channel allocation model that makes use of a period based re-allocation approach to cater for variations in traffic demand in each traffic class.

A detailed list of the outputs generated during this study as well as additional outputs related to this work is listed in Appendix C.

1.9 Outline of Thesis

This chapter provided a background of the problem considered in this study and the objectives of the project. The remainder of the thesis is organised as follows:

1. Chapter 2 provides literature reviews on various aspects considered in this study. The chapter first presents a basic overview of the impact of growth on mobile networks. The chapter then presents information retrieval and the impact of subscriber segmentation and their impact on mobile networks. Related work on feature extraction and classification, network planning and optimisation, channel allocation approaches, and the use of combinatorial optimisation solvers is then presented.

2. Chapter 3 presents the development of a proposed approach for feature extraction and classification of subscriber traffic classes in mobile networks based on the

traffic data extracted from a mobile network. The impact of using various feature extraction approaches is highlighted. Three approaches are focused on this study, the Empirical Mode Decomposition EMD approach, the Discrete Wavelet Packet Transform DWPT approach, and the Difference Histogram DH approach. A modified version of the DH approach is also presented.

3. The end goal of the subscriber classification/traffic class identification is the adaptive resource allocation approach proposed in this study to adapt to the varying demands of the identified traffic classes. Chapter 4 first presents the use of combinatorial solvers in solving optimisation problems, linear programming approaches which forms the basis for mixed integer linear programming approaches considered in this study, and approaches for solving mixed-integer linear programming approaches. The theoretical formulation of a proposed two-level hybrid channel allocation approach which is modelled as a mixed-integer linear programming MILP problem is then presented. The commercial optimisation solver, CPLEX,is used to obtain an optimal solution for the CAP. The results of the CPLEX solver are presented and recommendations are made.

4. Chapter 5 concludes the thesis. Based on the set out objectives, the achieved goals are highlighted. A number of recommendations for future work/further work to be considered is highlighted followed by final conclusions.

Three appendices are provided in this thesis. Appendix A provides related background on mobile networks. Appendix B provides related background on capacity optimisation in mobile networks. Appendix C provides an overview of publications related to this work and further publications that are indirectly related to this work.

Chapter 2

Literature Review

2.1 Introduction

The focus of this study can be separated into two primary aspects: the first focuses on feature extraction approaches based on which a classification approach is selected to determine subscriber classes in mobile cellular networks. The second focuses on radio resource optimisation based on the subscriber classes identified. This chapter provides related work on the feature extraction aspects, channel allocation, and optimisation approaches considered in this study.

2.2 Impact of Growth on Mobile Networks

With the advent of mobile cellular networks and the significant boom in the adoption of the technology worldwide, greater pressure is placed on mobile networks to ensure that they meet the rise in demand and GOS expectations from the subscriber point of view. From the network service provider point of view, the addition of capacity in the network needs to adopt an optimised approach for capacity improvement taking into account cost constraints. With mobile telecommunication networks being the choice of network roll outs in most developing countries across the world, wireless networks have witnessed an incredible boom with rates of growth far exceeding expectations. The boom in the telecommunications market in most developing countries has been fuelled by the ease of deployment and novel business models which are prevalent in these countries. One of the prominent factors that has influenced the rate of growth of mobile network subscriptions in developing countries has been the slow penetration of fixed line networks. A comparison between the growth in the mobile subscribers in developed and developing countries is illustrated in Figure 2.1.

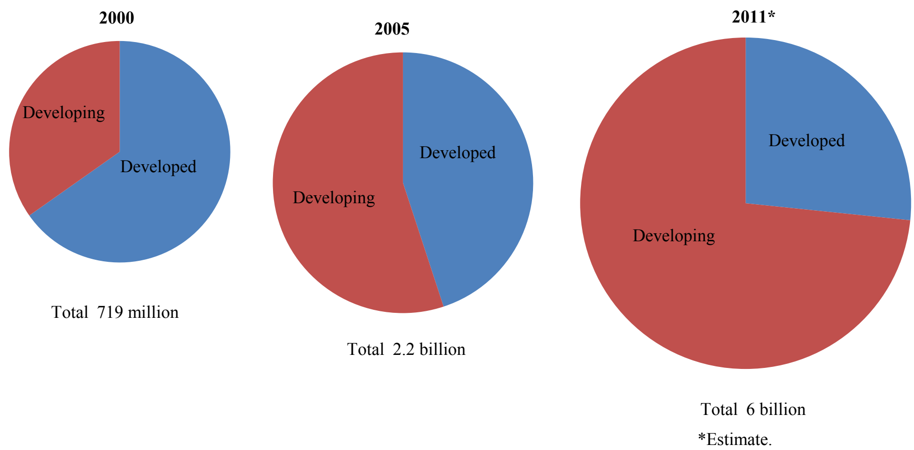


Figure 2.1: Comparision between Mobile Subscriber Growth, Developing vs. Developed Countries, 2000, 2005, 2011, source: ITU World Telecommunication/ICT indicator database

In any mobile networks, the number of subscribers in the network evolves over time as shown in the statistics in Figure 2.1. The rise in subscribers impacts on the required resources in the network required to sustain the rise in demand, and consequently, on the quality and expected GOS in the network. If the network does not evolve to meet the rise in demand, the quality of the network begins to degrade leading to blocked calls or dropped calls in the network. A typical example of this is illustrated in Figure 2.2. With increase in traffic, it is seen that congestion occurs in the network. To meet the increased congestion, the amount of allocated traffic channels needs to be increased. This is illustrated in Figure 2.3. Based on this problem, the implementation of an optimisation strategy could better adapt resources in the network to meet variations experienced in the network. The ability to identify traffic classes with particular behaviour traits that could aid in the capacity allocation process could be useful in achieving expected GOS requirements in the network.

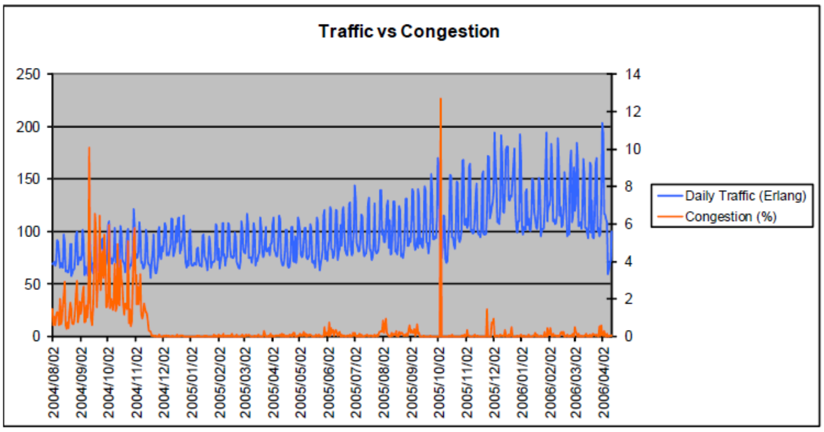


Figure 2.2: Comparison between Traffic Carried and Congestion in the Network

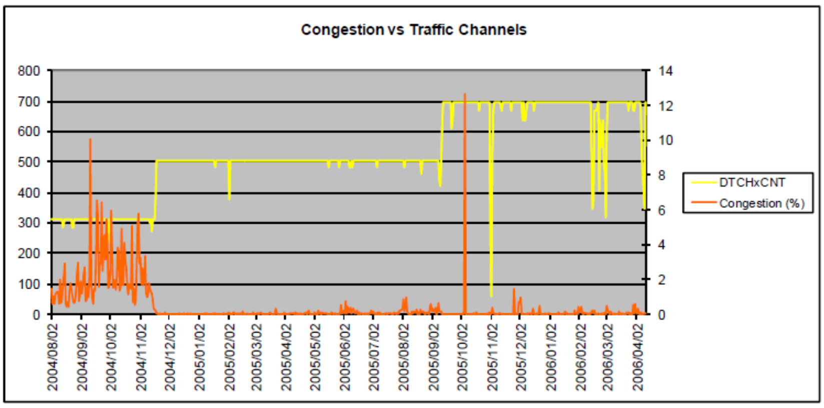


Figure 2.3: Comparison between Congestion and Allocated Traffic Channels

2.3 Information Retrieval in Telecommunication Databases

Telecommunication networks store vast repositories of data which provides the opportunity to utilise information extracted from these databases as a mechanism to optimise the network to bring about improvement in the network quality, and more importantly from the network operator point of view, to maximise the return on investment (ROI) from the network. With the explosion of the information age, the growth and the access to information across all disciplines of industry has been exponential. However, the explosive growth in many databases has far out paced the ability to interpret and digest this data [116]. With the large volumes of data that are generated on a daily basis, a growing need exists to be able to extract information that could be considered as useful knowledge. Due to the constant growth in demand for capacity in the network, a systematic approach to cellular network planning is crucial to maintain effective growth and returns on investments [105]. With the availability of relatively accurate data from a cellular network, cellular network planning that takes into consideration tele-traffic issues is vital for the long-term characterisation of subscriber behaviour [107].

With the drastically varying socio-economic status of various sectors of a typical developing country, traffic trends that are generated from various sectors of a network can vary tremendously. By determining various types of traffic classes that contribute to the traffic loads in a given network, the long term traffic trends can be predicted for the purposes of capacity planning. As highlighted previously, one of the objectives of this study is to develop a classification mechanism that is able to categorise various sectors of a mobile subscriber market into traffic classes and to then utilise the identified traffic classes for the benefit of a mobile network provider, for example, in their network planning strategy. As highlighted above, with the advent of database technologies over the past few decades, most modern enterprises today have data accumulated over the years residing in databases that store information about their customers, products, and the various services that they provide. Modern economies have become highly competitive with a focus on customers and services [116]. With the availability of large amounts of data available in a mobile network, mechanisms that are able to extract and convert the extracted information into useful information would be beneficial in determining the growth in demand for services in the network as well as determining demand anomalies that may arise in typical networks. The following section highlights the impact of subscriber classes on mobile networks.

2.3.1 Impact of Subscriber Classes in Mobile Networks

While mobile network coverage in most urban areas in developing countries is adequate, the coverage in many rural areas has been much lower. The rise in mobile network coverage has largely been contributed to by the growth in coverage in rural areas due to the lack of universal access and services (UAS) mechanisms [49]. As discussed in [49], the results of regression analysis comparing mobile subscriptions per 100 inhabitants and the gross national income per capita in US $ indicated that income plays a role in terms of penetration levels. It has been clear in many markets that competition has been a key driver in reducing call tariffs in many markets. Innovative business models such as the prepaid system has lead to greater stimulation of markets across Africa. As discussed in [49], varying prices depending on call types and call period during the day (peak,off-peak) impact on call usage by subscribers. In addition, the reduction in the cost of handsets could further stimulate the market especially in the case of low-income groups [49]. According to Gartner [31], 428 Million Mobile communication devices were sold worldwide in the 1st Quarter of 2011 which was a 19% increase year-on-year. With most rural communities being dependant on voice based services and innovative applications such as the M-PESA system launched by Kenyan mobile operator, Safaricom in March 2007 [49] and that is being extended to various other markets in Africa, mobile devices have become an integral part of most peoples everyday lives. However, the impact of the above is the pressure placed on mobile networks planners in meeting the rising demand for capacity. In addition to this, the challenge of catering for different subscriber classes in the network in many developing countries becomes a greater challenge due to varying service demands.

2.3.2 Customer Segmentation in the Telecommunication Industry

Businesses in the service industry need to have a better understanding of their customers if they are to provide better services to them as highlighted in [18]. By extracting information about customers, companies are able to make major decisions regarding re-organising a business, service offerings, marketing etc [113]. Market segmentation has shown various benefits over mass marketing strategies. According to [18], customer segmentation could be defined as the process of dividing customers into homogeneous groups on the basis of common attributes. Information about a customer provides the opportunity to expand as well as increase profitability into specific markets [18]. A common method for segmentation is the use of Clustering techniques. Cluster algorithms can be employed to discover groups of customers with common attributes [18]. Its use is appropriate when very little information is known about the categorisation structure of the underlying data [113]. However, the type of data used for clustering and the selection of meaningful attributes for the clustering approach play a critical role in the performance of the clustering process.

In the telecommunications industry, it is often useful to profile customers based on their patterns of phone usage. This information can be used to profile the customers and these profiles can then be used for marketing and/or forecasting purposes [113]. Various applications for segmentation have been proposed. By separating subscribers into customer groups with common behaviour, the provision of better calling rates to such a group, for example, could encourage greater usage of services. Identification of subscribers who are likely to adopt newer services is also useful in determining how best to offer attractive packages for such segments [84]. Mazzoni et al. investigate the characteristics of Italian cell phone users in [79]. A multi-dimensional segmentation approach is used to determine if differences exist among Italian mobile phone users leading to the identification of different market segments and secondly, to determine if it is possible to describe them using the multi-dimensional approach. In [61], Kianmehr et al. conduct cluster analysis to identify calling communities using information derived from call data records (CDR). In [98], factor analysis, clustering, and quantitative association is used to find service adoption patterns of segmented groups. From a network planning and optimisation point of view, by identifying market segments and considering that the network is not homogeneous but rather heterogeneous comprising of subscribers that behave differently, the network planning strategies employed for cells deployed in these segments has to be managed more effectively.

Various kinds of data are generated in a typical telecommunication network and include CDR data, network data describing the state of hardware and software components in the network, and customer data that provide information on customers [113]. A general overview of the Global System for Mobile (GSM) is provided in Appendix A. The OMC within such networks provides various measurements that are generated by different counters. These may be sorted into four domains: handover, quality of service, resource availability and usage, and traffic load [60]. Traffic load can be measured from these counters which provide information on when each available TCH is busy. In this study, traffic data extracted from the OMC of a typical mobile network is considered. In proposing a suitable approach for feature extraction and classification based on this data, the following section provides an overview of related work on feature extraction and classification.

2.4 Related Work on Feature Extraction and Classification Approaches

The use of signal processing approaches have been widely used for feature extraction and classification. However, one of the problems with traditional signal processing approaches is their inefficiency in providing sufficient information in the time domain. The choice of approaches such as the wavelet transform has shown the ability of the approaches to handle signals in short time intervals for high frequency components as well as long time intervals for low frequency components [108]. Wavelet based multi-resolution analysis technique (WMAT) approaches have also been shown to be useful in denoising multi-dimensional spatial/temporal signals containing steady/unsteady noise [42]. The empirical mode decomposition (EMD) approach has been shown to be a powerful tool in analysing composite, non-linear and non-stationary signals [73]. The difference histogram approach [109], a relatively new approach for feature extraction, has been shown to have benefits in terms of computational complexity and its suitability for real-time applications.

The choice of a suitable feature extraction approach is dependent on the ability of the method to handle the characteristics of the inputted signal. Various approaches have been demonstrated in literature that focus on suitable approaches that extract features for various applications. Eristi et al. in [28] use the wavelet transform and a state vector machine SVM) for the extraction of features from the impulse test response of a transform in time-frequency domain and classification of patterns inherent in the features extracted. In [108], Uyar et al. use a wavelet-based extraction approach based on norm entropy and a classifier based on a multi-layer perceptron for power quality (PQ) disturbance classification. It is shown that a reduced size in the feature vector and multi-resolution analysis is achieved with an increase in classification accuracy. Gaouda et al. use WMAT in [29] to detect and localise different power quality problems. Standard deviation curves are introduced at different resolution levels to classify different power quality problems. Peilin et al. use a combination of the wavelet transform (WT) and the SOLAR system (a sparsely connected multi-layer information theory based system) in [86] to achieve PQ classification. It is shown that the combination of the WT and the SOLAR system can achieve good PQ classification performance. Hu et al. use wavelet packet energy entropy and a weighted SVM in [44] to automatically detect and classify PQ disturbances. The WPT is used to denoise the digital signals and to decompose the signals to obtain common features. The SVM is then trained based on the features to make decisions regarding the type of disturbance. Wu et al. develop an automative generator fault diagnosis system using the discrete wavelet transform (DWT) and an artificial neural network (ANN) for classification in [117]. In [42], He et al. propose the use of WMAT for reducing noise induced by complex uncertainty in data cleansing and parameter estimation in river water quality simulation. Results show that the WMAT does not distort clean data and can effectively reduce noise in the polluted data. The DWT is used to reduce the complexity of the feature vectors.

Ekici et al. use the WPT and ANN in [26] for estimating fault locations in transmission lines. The energy and entropy criterion are applied to the wavelet packet coefficients to decrease the size of feature vectors. It is shown that the approach provides a reliable method for reducing data sets in size and enabling the estimation process to be quick and accurate. Youn et al. propose the use of the discrete wavelet packet transform (DWPT) and IIR polyphase filtering scheme in [119] for a fast spectrum sensing algorithm for cognitive radios. The DWPT is used to analyse interesting frequency bands based on multi-resolution while the IIR is used to reduce the complexity of the DWPT implementation. Reeve et al. use the WPT for the investigation of multi-scale temporal variability of beach profiles in [92]. Vatansever et al. perform power parameter calculations based on the WPT in [110]. From the above, the use of wavelet based signal decomposition is seen as a suitable approach for feature extraction especially in applications where signal behaviour prompts the use of multi-scale techniques for the extraction of features.

In [4], Bao et al. use the EMD approach to extract information of modulation from signals contaminated with noise. It is shown that the EMD method is capable of recovering the amplitude-modulated components from strong background noise in an adaptive way. Junsheng et al. propose a fault extraction approach based on EMD and an auto-regressive model (AR) in [56] for roller bearing fault diagnosis. The EMD method is used to decompose the non-stationary vibration signal of a roller bearing into a number of intrinsic mode functions (IMF) based on which the AR models of each IMF are established and regarded as feature vectors. In [73], Lin et al. propose an improved EMD method for signal feature extraction. The optimal envelope mean is obtained by an inverse EMD filter in the improved scheme with a new sifting stop criterion proposed to guarantee orthogonality of the sifting results. As an alternative to wavelet based approaches, the EMD based decomposition approach is thus seen as a suitable approach for feature extraction especially in applications where signals are contaminated with noise.

The concept of a difference histogram (DH) approach is introduced in [109] which is applied to a two rolling element bearing time series classification problem. The primary benefit of the approach presented in [109] is firstly the ease of implementation of the approach and secondly the reduced complexity of the approach. This could contribute to reduced complexity in the processing of large amounts of data as is the case of this study. It is shown in [109] that in some cases, the proposed approach performed better than alternative approaches to feature extraction and classification. As a result, the difference histogram approach is also considered in study to determine how well it performs when considering network traffic data and to determine the feature extraction capability of the difference histogram approach.

2.5 Mobile Network Planning and Optimisation

The second aspect of this study deals with the optimisation of radio resources in a mobile network based on features extracted from traffic data in the network. The strategy employed for network evolution to meet rising demand in the network should ideally take into account the minimum cost impact that changes in the network need to be made. In a staged manner, the first step would be to improve coverage to meet rising demand. Once maximum coverage has been reached, capacity limitation would be reached leading to a capacity limited network. To overcome this situation, the hardware and software aspects of the network are adapted to extend the capacity in the network. The first strategy is to begin BTS splitting into macro and micro base stations. The next strategy is to utilise dual bands to meet the capacity requirements through new frequency band implementation. This would be last option as this option is costly and impacts on the frequency planning of the network [70]. A summary of the network evolution is shown in Figure 2.4 [70].

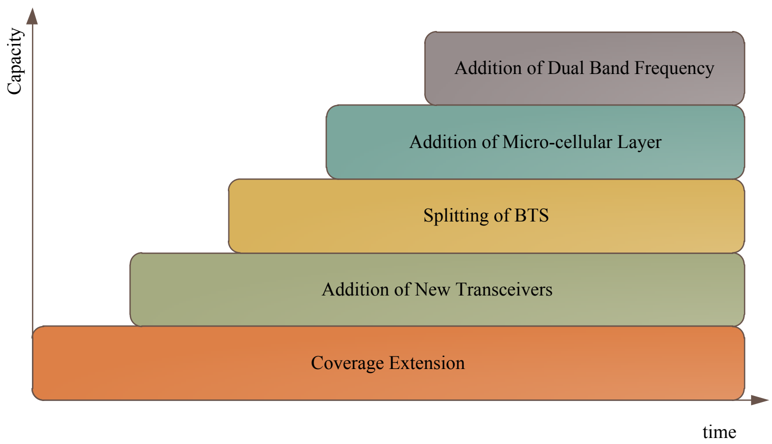


Figure 2.4: Network Evolution to Meet Rising Demand [70]

2.5.1 Related work on Network Planning and Optimisation

A number of studies have been conducted with a focus on improving and optimising the development of cellular networks. The focus of some of these methods has been on the development of strategies that make use of various algorithms to improve/optimise the development of networks. The overall goal of any planning strategy is to minimise the overall cost of the network design [41]. Once an area has been identified for service provision, the objective of any network design would be to develop a network that is optimised in terms of number of transmitters (Base Stations), capacity (Number of Subscribers) and frequency. The focus of optimum base station selection is highlighted in [85], [40], and [68]. The focus on Adaptive Base Station estimation is generate an optimised number of base station requirement as well as to develop an optimum base station location depending on subscriber densities that would establish a confluence to a specific location.

The use of Genetic Algorithms (GA) based on the concept of natural biological selection mechanism is highlighted in [85], [40], [100] and [68] focusing on the optimisation of various parts of the planning process such as determination of base station placement, cell reporting, and frequency optimisation. Genetic algorithms focus on applying operators to a random set of data that creates a new optimised population set based on a fitness function. The focus of these algorithms is to generate the best solution candidates and eliminate specimens that do not meet the required criteria. The benefit of GA algorithms is their relative ease of implementation and exploratory nature of the algorithm. The Tabu Search algorithm is illustrated in [100], [101] and [69] that are used for the purposes of cell reporting and cell planning activities. The Tabu search conducts a coarse examination of the solution space initially in a diversification process and focuses its search once candidate states are developed to produce local optimal solutions in a process of intensification. The Tabu search thus tries to eliminate the possibility of re-visiting iteration already considered. Whitaker et al.[115] present the concept of marginal cost of service coverage which represents the lowest rate at which infrastructure cost must increase to facilitate higher levels of service coverage. Cell-plan infrastructure efficiency is studied from two perspectives: establishing the effect of cell density on infrastructure cost of the network, and secondly, the influence of the effects of increasing infrastructure expenditure. Network planning can be investigated from an infrastructure cost-centric point of view addressing the balance between infrastructure costs and coverage for a wide range of subscriber densities.

Wireless service providers face the need to plan and rapidly evolve networks to meet subscriber demands which has an impact on the physical aspects of the network such as switching and radio equipment, available frequencies etc as described by Garcia et al. in [30]. From a planning point of view, the impact of network optimisation needs to focus on two aspects of the network: the access side and the core network side. Calin et al. discus a new approach for capacity planning for growing Code Division Multiple Access (CDMA) networks. They highlight how the approach has aided in faster and more accurate capacity planning cycles while balancing QoS and capital investment constraints [10].

Various related studies on the above have been conducted as shown in Appendix B. The solving of the BTS placement problem for non-homogenous traffic using GA, the consideration of the BTS problem for 3rd generation (3G) networks, and the use of combined GA and Tabu search method for the Node-B placement in 3G networks is highlighted.

2.6 Channel Allocation Strategies in Mobile Networks

Competition has driven the reduction in mobile prices in many African countries resulting in mobile network operators expanding their networks to cater for lower-income subscribers [49]. With the rise in demand for capacity in mobile networks and subscriber expectations on quality in the network, greater pressure is placed on the network provider to ensure that capacity provisioning and cost is optimised in terms of base station site provisioning and frequency allocations. The cost-efficiency of capacity planning and the deployment within the network has to ensure a strategy that focuses on providing sufficient capacity at any specific point in the network with the least amount of capital investment from the network provider [3]. The biggest challenge in network provisioning is to consider strategies that cater for the non-homogeneous traffic within networks. The traditional approach to network planning is to consider a theoretical expected network capacity, and to consider optimisation strategies to improve the allocated capacity as a result of variations in the network. However, many studies have shown the inefficiencies of this approach, for example [3],[35]. From a frequency allocation point of view, various approaches have been proposed to solve the frequency allocation problem (Ex. Fixed, Dynamic and Hybrid strategies). An overview of channel allocation strategies in mobile networks is provided in Appendix A. The following section provides an overview of related work on channel allocation approaches in mobile networks.

2.6.1 Related Work on Channel Allocation Approaches

Various studies have been conducted on the channel allocation problem (CAP). Del Re et al. [22] propose an efficient dynamic channel allocation technique that makes use of a cost function to conduct optimal selection and assignment of channels on demand. A mobility model is also derived to determine the effects of hand overs on network performance. Dong et al. [23] derive a dynamic-priority strategy called a two-step dynamic-priority (TSDP) strategy that adopts an optimal carrier-reuse pattern concept which is used to define an optimal frequency reuse strategy. Primary and secondary channels are defined with primary channels having higher acquisition priority compared to secondary channels. Jiang et al. [54] developed a general algorithm that guarantees mutual exclusion for a single resource. This is then applied and extended to the distributed dynamic channel allocation case and further address issues of deadlock resolution, dealing with multiple channels, design of efficient information structures and channel selection strategies. In [121], a dynamic channel assignment DCA technique for large-scale cellular networks (LCN) is presented that makes use of a noisy chaotic neural network. The LCN is first decomposed into a number of subsets and the DCA process performed independently on each subset to reduce signalling overhead. An energy function is then formulated to avoid interference between neighbouring subsets based on a real-time interference channel table.

In [7], the authors present a distributed dynamic resource (channel) allocation algorithm (DDRA). The algorithm is based on the mutual exclusion paradigm in distributed systems. The algorithm is run at each base station in which each base station allocates resources available at run time by communicating with neighbouring base stations to exchange information regarding channel utilisation. Cao et al. propose an efficient distributed channel allocation strategy in [11, 12]. They first implement a channel acquisition algorithm based on features of search and update strategies and integrate it with a channel selection algorithm that makes use of an optimal resource planning model. Chang et al. [17] propose a borrowing channel algorithm (BCA) with the objective of reducing channel blocking probability compared to borrowing with directional channel locking (BDCL) algorithms. In their approach, two phases are implemented: the first phase allocates call requests to the lowest numbered free nominal channels if available. If nominal channels are not available, non-nominal channels are allocated based on an impact-based borrowing strategy in which channels are borrowed from neighbouring cells. In the second phase, re-allocation of channels is performed to improve efficiency. This consists of two phases in which reallocation occurs for locked channels and reallocation for improved efficient channel reuse. In [95], a BCA approach is formulated as a combinatorial problem with a time-based simulation model developed. Three heuristic techniques are used to implement the DCA by considering an energy function which determines the strategy for choice of channels in a cell. In [94], a combinatorial evolution strategy is used to handle the channel allocation problem. Three allocation schemes, the DCA, HCA and the BCA are formulated as combinatorial optimisation problems for which a combinatorial evolution strategy is used to solve the problem. In [20] and [21], a channel management algorithm called the distributed load balancing algorithm with selective borrowing (D-LBSB) is proposed for mobile networks. The approach begins with fixed channel allocation to each cell. Allocation of additional channels is conducted based on identification of hot and cold cells which do not necessarily have to be neighbouring cells. The proposed algorithm makes use of a Markov model which is used to determine which cells are hot and the call blocking probability. Capone et al.[13] propose a new model for the CAP that accounts for the cumulative effect of interferes in a network. The approach partitions the service area into regions with the propagation characteristics defined based on signal levels received from each base station. The objective is to maximise the sum of traffic loads offered by ensuring the C/I ratios are above a threshold value. The problem is solved using a tabu search approach. In [118], two integer linear programming (ILP) formulations are utilised to determine an optimum channel assignment scheme from a pool of available channels. The two approaches consider formulations where channel re-assignment is allowed or not allowed and consider hard constraints such as co-site and adjacent channel constraints. In [78], a model that addresses the cellular system design problem as a complete model is considered. A mixed-integer linear programming (MILP) approach takes into consideration the base station placement problem, the channel assignment problem and the base station-to-fixed network connection problem. The objective of unifying the above is to determine the trade offs that can be achieved in obtaining higher quality in the solution of the network design problem. In [33], a meta-heuristic approach is proposed to minimise the total interference experienced in a mobile network. The proposed algorithm is based on the greedy randomised adaptive search procedure (GRASP). The objective of the frequency allocation problem proposed is to minimise both the co-channel and the adjacent channel interference. In [120], an efficient load-balancing algorithm for channel assignment in mobile cellular networks is designed and analysed. The proposed approach employs a two-threshold cell selection scheme in which the fixed channel allocation is utilised on an underlying level and the available channels are dynamically balanced during run time. Two thresholds are utilised to classify cells: light and heavy to categorise cells into light, moderate, and heavy cells based on the number of available channels in the cells. A heavy cell is enabled to borrow cells from light cells or co-channel cells based on the state of the potential cells. In [111], an evolutionary strategy is used to optimise the channel assignment problem. A HCA that makes use of the fixed reuse distance is proposed to conduct D-DCA. In [62], the channel allocation problem is solved by using simulated annealing to conduct the allocation of nominal channels. In [43], the efficiency of various channel allocation schemes is considered. The fixed-uniform channel allocation (FUCA), fixed non-uniform channel allocation (FNCA), dynamic channel allocation (DCA), and dynamic frequency/time channel allocation (DFTCA) are evaluated. It was shown that as the total arrival rate of traffic increases, the efficiency shown by the DFTCA and the DCA algorithms over the fixed allocation algorithms decreases. When the traffic loading was fixed and as the distribution of the load became more uneven, the efficiency of the fixed allocation algorithms decreased.

2.7 Approaches for Solving Combinatorial Optimisation Problems

As highlighted above, various aspects of the network planning and optimisation above such as the BTS placement problem and the CAP problem can be considered to be combinatorial optimisation problems (COP) that can be solved using combinatorial optimisation solvers. The objective of a COP is to determine values for discrete variables such that an optimal solution with respect to an objective function is identified subject to problem specific constraints [90]. In selecting a suitable approach for the optimisation problem considered in this study, an overview of related work on the use of combinatorial optimisation solvers is given in the next section.

2.7.1 Related work on the use of Combinatorial Optimisation Solvers

A number of studies have been conducted that consider the benefits of utilising $linear-programming$ approaches and $meta-heuristic$ based approaches. In [5], Biskas et al. consider a comparison of two meta-heuristic approaches (enhanced genetic algorithm and particle swarm optimisation) with two mathematical programming approaches for solving the optimal power flow problem in power systems. In [99], a comparison between the results obtained between different meta-heuristic approaches (tabu search, genetic algorithm, and simulated annealing) and the results obtained from a mixed-integer programming (MIP) solver to solve global planning problems in UMTS networks. Combined integer linear programming (glsilp) and meta-heuristic studies have been conducted to create hybrid approaches for combinatorial optimisation as discussed in [90] and [102]. In [114], a new heuristic algorithm which aims at improving Gomory mixed-integer cuts in the mathematical optimisation system (MOS) MIP solver. The MOP MIP solver is a high performance system for solving large scale linear and mixed integer programming problems [114]. In [19], a customised branch-and-bound technique is proposed to solve the resource constrained shortest path problem in the optimisation of sensor locations along freeway corridors. Numerical experiments along an urban freeway corridor demonstrated that the proposed model was successful in allocating loop detectors to improve the accuracy of travel time estimation. In [37], a new mixed-integer programming model is proposed to determine the optimal sink locations and information flow paths between sensors and sinks when sensor locations are given. Two sets of models are considered. The first considers the energy-aware models that minimises the total routing energy. The second considers the financial aspect with the objective of minimising the total cost [37]. In [74], a global optimisation algorithm for solving a mixed transportation network design problem (MNDP) is proposed. The MNDP is approximated as a piece-wise linear programming problem and then converted into a mixed-integer linear programming problem [74]. The optimisation algorithm considers a cutting constraint method for solving the MILP problem [74]. In [81], three MIP formulations are made for the k-connected minimum power consumption problem which consists of finding a power assignment for nodes in a wireless network such that the result network topology is k-vertex connected while ensuring that the total power consumption in the network is minimised. It is shown that optimal solutions are obtained for moderately sized networks using a commercial solver. In [64], the use of MIP is proposed for improvement of the QoS based web service (WS) discovery. QoS based WS discovery has been recognised as the main solution for filtering and selecting between function equivalent WSs in various repositories [64]. The use of MIP is proposed for the matchmaking process instead of Constraint Programming (CP) based approaches. It is shown that the MIP outperforms the CP based approach and was found to exhibit a more stable performance [64]. In [82], a mixed integer linear programming (MILP) approach is implemented in a General Algebraic Modelling System for the optimal operation of energy management in small power systems. The optimal operation of wind turbines, solar units, fuel cells, and a storage battery are searched using the MILP taking into consideration the timing to maximise the performance of supply [82]. In [6], the use of MILP models of increasing complexity are used to solve the unit commitment problem for the optimal scheduling of multi-unit pump storage in a hydro-power station. Based on the above, Mixed-Integer programming approaches are seen as a suitable approach for obtaining optimal solutions for COP type problems. A more detailed analysis is provided later in this thesis.

2.8 Conclusion

This chapter provided a basic summary of related work on the two main problems considered in this study. The first considers feature extraction and classification in mobile networks. A short background on the factors that prompt the need to implement optimisation approaches in mobile networks is first highlighted. Customer Segmentation has been shown to be a useful tool for managing services provided by businesses to consumers. By segmenting customers into identifiable groups, better resource provisioning can be made to these groups. This is the primary objective of conducting the feature extraction in and classification part in this study. Various related work on feature extraction and classification was presented which serves as the basis for the proposed approach considered in this study.

The second aspect of the study deals with network optimisation approaches. An overview of related work on network planning and optimisation approaches is highlighted. Various optimisation approaches utilised for solving of network planning and optimisation problems is highlighted. The channel allocation problem is highlighted. Related work on the solving of the channel allocation problem is highlighted. Of particular interest in this study is the hybrid-channel allocation schemes (HCA) which provide mechanisms to consider both FCA approaches and DCA approaches. The last part of the chapter provided an overview of related work on the use of Combinatorial Optimisation Solvers which forms the basis for proposing a new model for the solving of the CAP in this study. The following chapter presents the development of a feature extraction and classification approach for mobile cellular networks.

Chapter 3

Feature Extraction for Subscriber Classification in Mobile Cellular Networks

3.1 Introduction

In developing a radio resource optimisation strategy that takes into account mobile subscriber behaviour, the first phase of this study first considers the development of a subscriber classification approach. This chapter presents the proposed approach that considers feature extraction and classification based on extracted features. A preliminary analysis is first conducted. This is followed by a more detailed analysis of the proposed approach and presents the potential of the approach in segmenting subscribers into distinct traffic classes.

3.2 Selecting a Suitable Feature Extraction Approach

It was highlighted in the previous chapter that various forms of data are generated on a daily basis in a typical telecommunication network. The OMC in a mobile cellular network provides various measurements which are measured at various intervals during the day. These measurements represent a vast repository of information regarding network status and performance and contains vital information about the subscriber behaviour in the network. Time series traffic data obtained from the OMC is considered as input for the feature extraction process. However, such time series data carry an extremely large amount of data in which relevant information being searched for is often difficult to find [76]. The primary goal of signal processing approaches applied to feature extraction is to provide underlying information on specific problems[96]. In the development of a suitable feature extraction and classification approach, the choice of a suitable feature extraction approach is crucial. Feature extraction forms one of the most important stages in the signal classification process. If appropriate features are not selected well for a given classification problem, the performance of the classification may not be satisfactory [47].

Signal processing techniques have been widely used for feature extraction and classification in various applications as demonstrated in the literature review considered in chapter 2. The extracted features using signal processing techniques provide underlying information that can aid with decision making [96]. The choice of the approach selected is dependant on the input signal and the ability of the feature extraction approach to handle the characteristics of the signal. For example, features such as amplitude levels in the time domain can be easily extracted but may be susceptible to noise [96]. The energy concentration in the time-frequency domain can lead to more robust feature extraction and accurate classification though it may involve more number of operations [96]. In determining the most suited signal processing approach for feature extraction, the apriori information of the behaviour of the input signal must be known. The use of parametric models is possible if an accurate model of the signal is available [96].

However, in the case of non-stationary signals, a consistent parametric model may not exist. Most traditional signal processing approaches are based on linear and stationary assumptions [97]. Data in the real world are traditionally non-linear and non-stationary. In these cases, the time domain may lack the frequency description or the frequency domain may lack the description of the variance of the spectral information with time [96]. In the time-frequency domain, the energy concentration along the frequency axis at a given instant of time is determined [96]. A summary of some typical approaches for feature extraction and classification is shown in Figure 3.1 [96]. As highlighted above, time and frequency domain approaches can be used to decompose signals to reveal signal properties providing a path for representation of a signal in a sparse manner [76].

This makes the processing faster and simpler since a smaller number of coefficients are obtained which reveal more information regarding the signal.

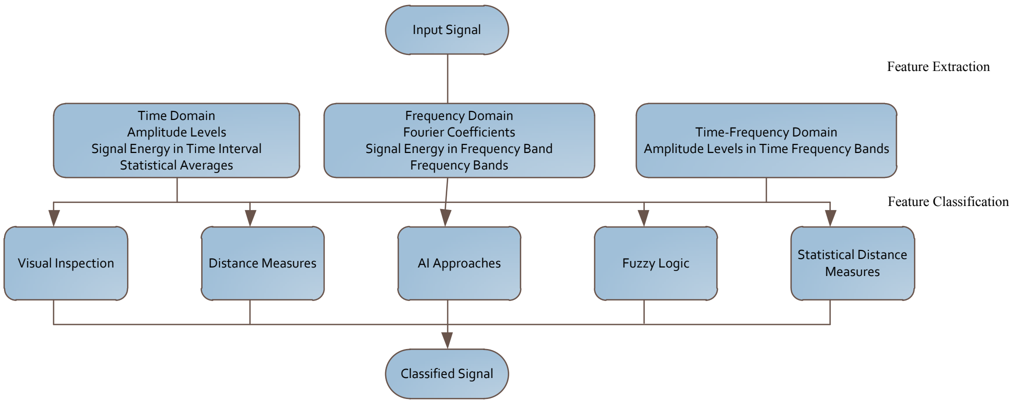


Figure 3.1: Signal Processing Approaches for Feature Extraction and Classification

Considering the Fourier analysis of a signal [76], the Fourier analysis represents a finite energy function as the sum of sinusoidal waves $e^{i\omega t}$ such that

$$f(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \hat{f}(\omega) e^{i\omega t} d\omega \tag{3.1}$$

$\hat{f}(\omega)$ of each sinusoidal wave $e^{i\omega t}$ is equal to its correlation with $f(t)$ and is referred to as the Fourier Transform given by

$$\hat{f}(\omega) = \int_{-\infty}^{\infty} f(t) e^{-i\omega t} dt \tag{3.2}$$

If the input signal is linear and time-invariant or uniformly regular, Fourier analysis provides straight forward answers. However, the Fourier transform becomes inefficient in extracting transient information of non-stationary signals [27]. The Fourier transform of a signal, for example, cannot depict how the spectral content of the signal changes with time [96]. Wavelets, on the other hand, are well localised with few coefficients required to represent the local transient structures contained in a non-stationary signal [76]. Contrary to the Fourier transform, a wavelet basis defines a sparse representation of piece-wise regular signals which may contain transients and singularities of the inputted signal.

3.2.1 Multi-resolution Based Approaches

The uneven distribution of signal energy in the frequency domain has made signal decomposition an important practical problem [2]. The decomposition of a signal spectrum provides two important aspects in signal analysis. These include the ability to monitor the signal energy components within sub-bands and the sub-band decomposition through multirate signal processing which leads to multi-resolution signal decomposition [2]. Figure 3.2 represents a dyadic tree illustrating the concept of decomposition of a signal. The signal is split into low and high frequency sub-bands and this process can be continued for upto K levels [2].

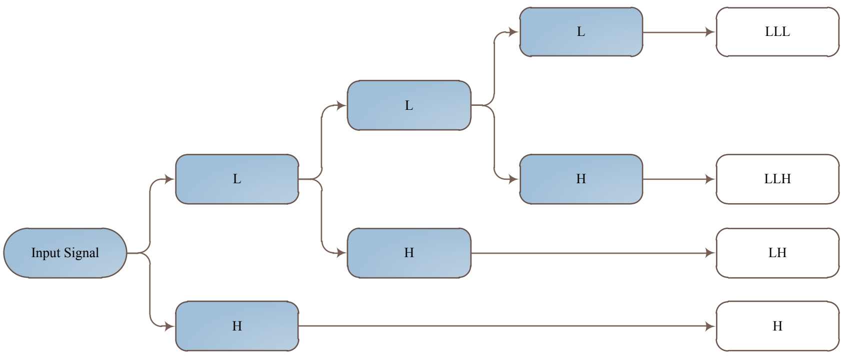


Figure 3.2: Dyadic Tree Representing Low-Pass(L) and High-Pass(H) Filters

The wavelet transform makes it possible to apply multi-resolution analysis of a signal being studied. Wavelet bases reveal the regularity of signals through amplitude coefficients using a fast computational algorithm. As described by Mallat in [76], the wavelet transform decomposes signals over dilated and translated wavelets. For $f \in L^2(\mathbb{R})$, the partial sum of wavelet coefficients can be represented as $\sum_{n=-\infty}^{\infty} \langle f, \psi_{j,n} \rangle$ where $\psi_{j,n}$ can be interpreted as the difference between two approximations of f at resolutions

2^{-j+1} and 2^{-j}. Multi-resolution approximations provide a mechanism to compute the approximation of signals at various resolutions with orthogonal projections on different spaces. On the basis of localised functions in the time scale, one associates the family of wavelets $\psi_{j,n}(t)$ [39,76] generated by translations and dilation of $\psi(t)$ such that

$$\psi_{j,n} = \frac{1}{\sqrt{2^j}}\psi(t - 2^j n/2^j), (j, n) \in \mathbb{Z}^2 \tag{3.3}$$

The processing of only the relevant details of a particular application is made possible by adapting the signal resolution. The approximation of a function f at a resolution 2^{-j} is specified by a discrete grid of samples that provides the local averages of f over neighbourhoods of size proportional to 2^j. A detailed mathematical analysis of the multi-resolution formulation is presented in [76].

An alternative means of separating a multi-component signal into mono-component constituents is the EMD approach. The EMD approach splits the signal into mono-component constituents through progressive sifting to yield empirical bases consisting of IMF components [97]. A more detailed analysis of the approach is given later in this chapter.

3.2.2 Time Series Based Analysis

The traffic signals extracted from the OMC in a mobile network may be considered to be of a time series nature. A Time Series (TS) can be viewed to consist of a variable Y that is a function of time t such that $Y = f(t)$ [40]. The primary goal of knowledge discovery in time series data is to detect interesting patterns from the time series data that maybe helpful for humans in better recognising the regularities in the observed variables thereby improving the understanding of systems [53]. As stated in [53], when dealing with time series data, there are two main objectives:

1. The prediction of future behaviour based on past experiences.
2. The description of the time series data.

Time series data sets are of very high dimensions which presents a major challenge since most non-trivial data mining and indexing algorithms degrade exponentially with dimensionality [34]. Time series segmentation has been studied quite extensively in literature. The objective of segmentation approaches is to approximate a sequence of values using piece-wise approximation approaches of line segments that effectively capture features of the underlying data. Some of the approaches considered for dimensionality reduction include the use of the Discrete Fourier Transform (DFT) in [1], the piece wise aggregate approximation approaches (PAA)[25] proposed by Keogh et al., the use of online segmentation approaches as shown in [58], the symbolic aggregate approximation approach (SAX) as shown in [72], adaptive piecewise constant approximation (APCA) proposed in [15], the use of Singular Value Decomposition in [16], and the use of the DWT as shown in [63]. Van Wyk et al. propose a Difference Histogram approach in [109] which extracts difference histogram bins as features based on occurrences of segments of increases. A more detailed analysis of the approach is given later in this chapter.

3.3 Background on Feature Extraction Approaches Considered in this Study

In this study, various feature extraction approaches are tested with traffic data extracted over a selected time period to determine their suitability for determining traffic classes in the network. The input signals are first tested with a single approach to determine the potential of the above approach in creating separation between the traffic signals into traffic classes. Based on the first analysis, a second phase consisting of a more detailed analysis is conducted to determine more accurate signal decomposition approaches that could potentially yield greater accuracy in the splitting of traffic signals into distinct traffic classes.

As discussed in Section 2.4, the choice of a suitable feature extraction approach is dependent on the ability of the method to handle the nature of the input signal. It was shown that various approaches have been considered for various applications that consider non-stationary, non-linear data. Due to the multi-scale characteristics of the Wavelet based approaches and the EMD approach, considers both approaches due to the nature of the traffic data considered in this study. In addition, the relatively new Difference Histogram approach is considered due to the simplicity of the approach and the suitability of the approach to real-time data. In this study, the Difference Histogram approach proposed by Van Wyk et al. in [109] is further modified, and the performance of the modified algorithm compared with the results of the original difference histogram approach. To better orient the reader to the reader to the prosed approaches, a brief overview of each of the above approaches is given in the following sections.

3.3.1 The Empirical Mode Decomposition Approach

Based on Rilling in [93], the basis for the EMD approach is to consider oscillations in signals at a very local level. A local *detail* (high frequency component), $d(t)$, may be considered which corresponds to the oscillations terminating at two minima(t_- and t_+) and that passes through the maximum which may exist between them. A corresponding local *trend* (low frequency component), $m(t)$ may be defined such that for signal $x(t) = m(t) + d(t)$ [93]. This process is effected in an iterative manner for all oscillations that the signal composes of [93]. The basic algorithm for the EMD approach as described in [93] can be considered to comprise of the following steps:

1. Identify extrema of $x(t)$.
2. Interpolate between minima/maxima giving an envelop, e_{min} with respect to e_{max}.
3. Compute mean, $m(t) = (e_{min}(t) + e_{max}(t))/2$.
4. Extract detail, $d(t) = x(t) - m(t)$.
5. Iterate on the residual, $m(t)$.

When the detail signal, d(t) can be considered to have a zero-mean after a refining process (*sifting process*), the detail is referred to as an IMF [93]. An IMF must satisfy the following conditions [4]:

1. In the whole data set, the number of extrema and the number of zero crossings must either be equal or differ at most by one.
2. At any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima must be zero.

Since IMFs act as base functions and are data specific, they are directly derived from the signals to be analysed making them fully adaptive to filter out signals with irregular structures [4].

3.3.2 Wavelet Based Approaches

The main aim of multi-resolution analysis is to partition a data series into independent components of differing scales so that the variations in the data series can be investigated over the scales [92]. The discrete wavelet transform (DWT) is derived from the continuous wavelet transform (CWT). The DWT has the advantage that it does not shift and scale continuously. It also has the advantage that it decomposes the input signal into an approximation, which are low frequency components, and the details, which are high frequency components [117]. By creating filter banks that comprise of high-pass and low-pass filters, the detail at each scale and a scaling function, which represents the remaining energy, can be identified [92]. The DWT uses low and high pass filters, $h(k)$ and $g(k)$, to divide an input signal, $f(k)$, into low and high frequency components [27]. The low pass filter is determined from the scaling function while the high pass filter is determined from scaling and wavelet functions [27]. The scaling and wavelet functions, $\phi(k)$ and $\psi(k)$, may be described as given by Eristi in [27] as:

$$\psi(k) = \sqrt{2}\sum_{n} g(n)\phi(2k-n) \tag{3.4}$$

$$\phi(k) = \sqrt{2}\sum_{n} h(n)\phi(2k-n), \tag{3.5}$$

where n represents the number of samples in the input signal. The DWT defines a relationship between the approximations, A_j , and the detail, D_j between two adjacent levels as [27]:

$$A_{j+1}(k) = \sum_{n} h(n-2k)A_j(n) \tag{3.6}$$

$$D_{j+1}(k) = \sum_{n} g(n-2k)A_j(n), \tag{3.7}$$

where j represents the frequency band level. A given input signal, $f(k)$, is expanded iteratively in terms of its orthogonal basis of scaling and wavelet function [27]. The input signal can thus be considered to consist of one set of scaling functions and several set of wavelet functions as defined in [27]:

$$f(k) = \sum_{n} A_1(n)\phi(k-n) + \sum_{n}\sum_{j=1} D_j(n)2^{-j/2}\psi(2^j k - n) \tag{3.8}$$

The primary difference between the DWT and the DWPT is that the DWPT splits not only the approximation space but also the detail space [26, 119]. It has been shown that better frequency resolution is obtained when using DWPT which is able to extract more features from the input signal [26]. In the DWT, the wavelet and scaling functions are applied only to the wavelet coefficients generated at each iteration. This serves as one of the motivations for selecting the approach in this study. In the DWPT, during each iteration, the wavelet and scaling functions are applied to both the wavelet coefficients and the scaling coefficients [92]. The DWPT can be described based on [110] as:

$$W_{2n}t = \sqrt{2}\sum_{k=0}^{2U-1} g[k]W_n(2t-k), \tag{3.9}$$

and

$$W_{2n+1}t = \sqrt{2}\sum_{k=0}^{2U-1} h[k]W_n(2t-k), \tag{3.10}$$

where $W_0(t) = \phi(t)$ and $W_1(t) = \psi(t)$ represent the scaling and wavelet functions respectively, and U is the half-length of the decomposition window. Figure 3.3 illustrates the variation in the decomposition process between the DWT and DWPT approaches. Considering a signal with $N = 2^L$ samples that undergoes an $s - level$ decomposition, 2^s packets are created with $N/2^s$ coefficients [110]. Considering that $p_s^2 m[k]$ represents the wavelet packet (WP) coefficient at node $2m$ at point k for $s = 0, 1, \ldots, L$ and $m = 0, 1, \ldots, 2^{s-1}$, then $x(t)$ can be computed based on the WP coefficients as [110]:

$$x(t) = \sum_{k=1}^{N/2^s} p_s^0[k].\,\varphi_{s,k}(t) + \sum_{m=1}^{2^s-1}\sum_{k=1}^{N/2^s} p_s^m[k].\,\psi_{s,k}^m(t) \tag{3.11}$$

3.3.2.1 Choice of Analysing Wavelet

A number of wavelet functions are defined for wavelet based applications. The application of wavelet bases exploit their ability to efficiently approximate classes of functions with few non-zero wavelet coefficients. The design of the wavelet, ψ, should be optimised to ensure that a maximum number of wavelet coefficients are close to zero.

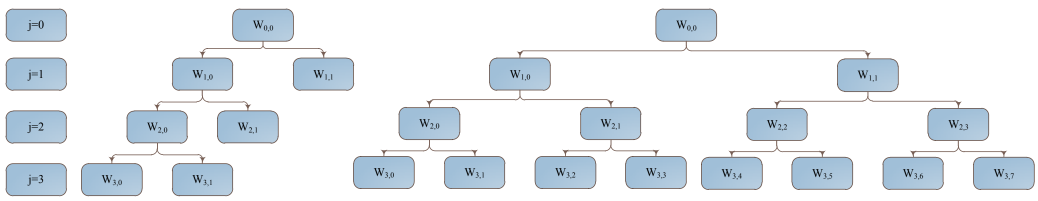


Figure 3.3: Comparison between DWT and DWPT flow diagram

According to Mallat [76], a function f has a few number of non-negligible wavelet coefficients depending on whether the high-resolution wavelet coefficients are small. This depends on the regularity of f, the number of vanishing moments of p, and the size of its support. If a wavelet ψ has p vanishing moments, then the size of support is atleast $2p-1$. The generation of sub-trees in a complete tree structure of the discrete wavelet packet transform, the number of different orthonormal bases B_L is equal to the number of different admissible binary trees of depth of at most L. Based on this, the number of wavelet packet bases satisfies the condition $2^{N/2} \leq Blog_2N \leq 2^{5N/8}$ [76]. Based on the above, entropy measures could be used to determine if the splitting to new levels is of interest so as to obtain minimum-entropy decomposition. A comprehensive list of wavelet families with wavelet functions and orders is listed in table 3.1 [89].

Table 3.1: Wavelet Family, Functions and Order [89]

Wavelet Family	Wavelet Functions and Order
Daubechies	db1 (haar),db2,db3,db4,db5,db6,db7,db8,db9,db10.
Symlets	sym2,2ym3,sym4,sym5,sym6,sym7,sym8.
Coiflet	coif1,coif2,coif3,coif4,coif5.
BiorSplines	bior1.1,bior1.3,bior1.5,bior2.2, bior2.4,bior2.6,bior3.1,bior3.3,bior3,5,bior3.7, bior3.9,bior4.4,bior5.5,bior6.8.
ReverseBior	rbio1.1,rbio1.3,brio1.5,rbio2.2, rbio2.4,rbio2.8,rbio3.1,rbio3.3,rbio3.5,rbio3.7, rbio3.9,rbio4.4,ribo5.5,ribio6.8.
Discrete Meyer	dmey.

3.3.3 The Difference Histogram Approach

The difference histogram approach proposed by Van Wyk et al. in [109] is considered in this study for feature extraction in mobile network traffic data. The difference histogram approach presents a new approach for feature extraction that is inexpensive, easy to implement and ideal for time series feature extraction. Consider a time series $\phi(n)$ consisting of data points such that $\phi(n) = x_1, x_2, \ldots, x_N$. A difference histogram, Ω, may be defined as a scaled representation of a number of occurrences of the lengths of segments of increase in a block of N samples of the discrete time series, $\phi(n)$. A segment of increase is defined as a group of consecutive samples in the discrete time series $\phi(n)$ such that $\phi(n+1) - \phi(n) > \phi(n) - \phi(n-1) - \varepsilon$, where ε is a tolerance parameter, $\varepsilon > 0$. The tolerance parameter is selected such that the distance measures are maximised between $\Omega_i, \forall i = 1, \ldots, k$, where Ω_i represents the difference histograms of k classes obtained from $\phi(n)$ [109]. The objective of the algorithm is to measure segments of increase based on the above condition and increment the relevant histogram bins ($\Omega(k)$) for identified classes. Algorithm 1 highlights the basic approach followed by the difference histogram proposed in [109].

Algorithm 1 Original Difference Histogram Approach [109]

Require: $initialise : \varepsilon, k = 0, \overline{\Delta} = 0, \Omega = 0$
  for $n = 2$ to N **do**
    $\Delta \leftarrow \Phi(n) - \Phi(n-1)$
    if $\Delta > \overline{\Delta} - \varepsilon$ **then**
      Increment k
    else
      Increment $\Omega(k)$
      $k \leftarrow 0$
    end if
    $\overline{\Delta} \leftarrow \Delta$
  end for
  scale Ω

In this study, a variation to the above algorithm is considered. In comparison to the original algorithm in which the frequency of the segments of increase is measured and stored in difference histogram bins, in the alternative approach, the lengths of the individual segments of increase is measured and stored in each difference histogram bin. The variation in the approach is shown in algorithm 2. To demonstrate the variation between both approaches, both methods are tested for feature extraction and classification.

Algorithm 2 Varied Difference Histogram Approach

Require: *initialise* : $\varepsilon, k = 0, u = 0, \Delta = 0, \Omega = 0$
  for $n = 2$ to N **do**
    $\Delta \leftarrow \Phi(n) - \Phi(n-1)$
    if $\Delta > \overline{\Delta} - \varepsilon$ **then**
      Increment k
    else
      $\Omega(u) = k$
      Increment u
      $k \leftarrow 0$
    end if
    $\overline{\Delta} \leftarrow \Delta$
  end for
  scale Ω

3.3.4 Dimensionality Reduction for the Improvement of Classification

In pattern classification problems, it is desired that the dimensionality of the pattern representation level be kept as small as possible to increase the accuracy of the classification and reduce the computation load and time [28]. To improve the accuracy of the classification process, it is desired that the detail coefficients and approximation coefficients obtained from a wavelet based transform, for example, are not inputted directly into the classification process. A method of dimensionality reduction is usually employed on the coefficients. A summary of possible feature extraction approaches for dimensionality reduction is presented in table 3.2 which is adapted from [28]. In this study, RMS, Shannon-Entropy and Log-Energy Entropy were considered.

Table 3.2: Feature Extraction Techniques [28]

No.	Feature Extraction Technique	Formulation
1.	Mean	$\mu = \frac{1}{N}\sum_{j=1}^{N} d_{ij}$
2.	Standard Deviation	$\sigma^2 = \frac{1}{N}\sum_{j=1}^{N}(d_{ij} - \mu)^2$
3.	Root Mean Square	$rms = \sqrt{\frac{1}{N}\sum_{j=1}^{N} d_{ij}^2}$
4.	Energy	$energy = \sum_{1}^{N} \lvert d_{ij}\rvert^2$
5.	Shannon-Entropy	$entropy = -\sum_{j=1}^{N} d_{ij}^2 log(d_{ij}^2)$
6.	Log-Energy Entropy	$log - energy = \sum_{j=1}^{N} log(d_{ij}^2)$

3.4 First-Phase Development of a Feature Extraction and Mobile Cellular Network Subscriber Classification Approach

The establishment of a direct relationship between the traffic generated by mobile subscribers in a cell in a mobile network and the socio-economic characteristics of the subscribers using a service provided by the cell is in most cases difficult to assess. The network data measured from the OMC represents counters that measure the total traffic carried in a cell over a period of time. The association of this data to the socio-economic relationship of a subscriber is not made directly at this level. However, knowledge of environments being studied can help identify key underlying features that can provide indications of common attributes that better describe subscriber behaviour. In developing the proposed approach for subscriber classification based on traffic generated from the network, the traffic carried per cell in mobile cellular networks is considered as input signals. Signal decomposition and feature extraction is conducted on these signals. It is crucial that the selected feature extraction approach is able to adapt to the non-linear nature of the traffic data.

3.4.1 Mobile Cellular Network Traffic Data Characteristics

The traffic load in a typical mobile network measured from the OMC in a network can provide information on traffic carried by each available TCH. In this study, traffic data sets were obtained from different geographic regions in South Africa from two different network operators. In the first data set obtained from the first network provider, the traffic data was grouped into three broad traffic classes based on their geographical location and the type of activity at the location: Central Business Districts (CBD), traditional suburban areas (SUB), and township areas (TWN) prevalent in most South African urban areas. Samples of the typical traffic distribution carried by three different cells in the above three traffic classes is shown in figure 3.4. The traffic measured represent traffic samples comprising of daily traffic samples measured during the busy hour which was measured over a two year period. A typical sample of the traffic data used is shown in table 3.3. Considering the traffic classes identified, in typical suburban type areas, mobile users usually have on average a medium to high income and traditionally have access to formal banking systems. As a result, the likelihood of subscribers being on a post-paid contract is higher compared to prepaid subscribers. On the other hand, in general, the average income for subscribers in a typical township could generally be low. Due to lower income brackets and the lack of access to formal banking systems, the percentage of prepaid contracts are generally higher. CBDs in the South African context are business centres mainly composed of corporate offices. Workers belonging to various levels of the socio-economic scale migrate from suburbs and the townships to CBD areas on a daily basis for work. The characteristic behaviour of the traffic in CBD areas could be well described with the traffic load sampled on an hourly basis. One can observe large traffic during the working hours of the day and almost no traffic before and after working hours. Public holidays can also have an observable effect on the traffic and is a periodic yearly pattern. The periodogram (estimation of the power spectral density of a signal) generated for each traffic class identified above is shown in figures 3.5, 3.6 and 3.7. The periodogram in this case is only used to illustrate the periodicity prevalent in the traffic data which correspond to observable patterns in the data. From the above, comparing the suburban signals and the township signals, it can be observed in the spectrum analysis that the intensity of the peaks in relation to the signal itself is considerably higher for suburban areas when compared to the township areas. As discussed in [66], from a signal processing point of view, the Signal-Noise-Ratio (SNR) in the township area is lower than that in the suburban area. This indicates that the spectrum in the township area is flatter. Based on this analysis, it can be concluded that by separating the frequency patterns, it is possible to distinguish between a suburb and a township area. This highlights the potential of the frequency domain decomposition of the traffic signal and the potential of the approach in the extraction of features.

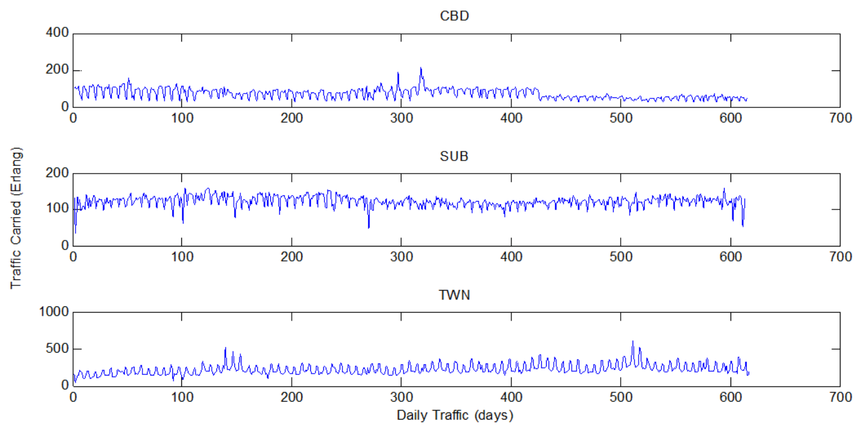


Figure 3.4: Traffic Sample for CBD, SUB, TWN classes

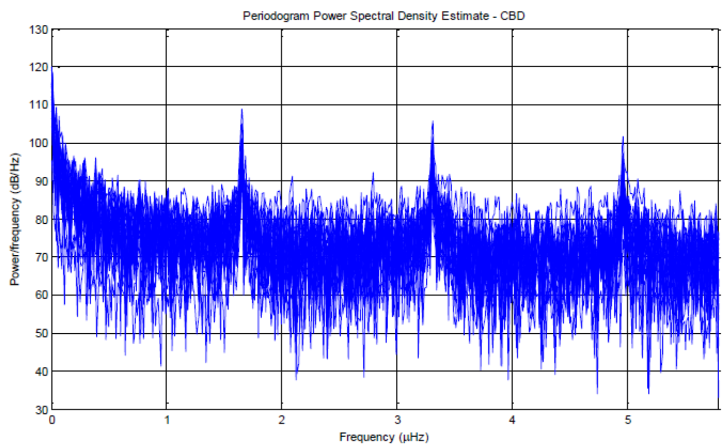


Figure 3.5: Periodogram for CBD Area

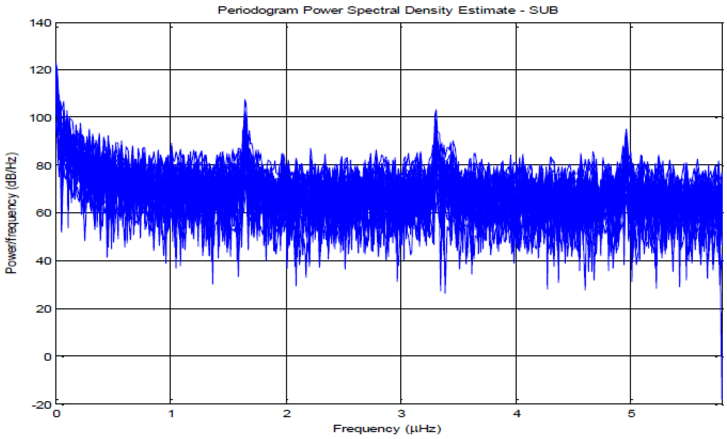


Figure 3.6: Periodogram for SUB Area

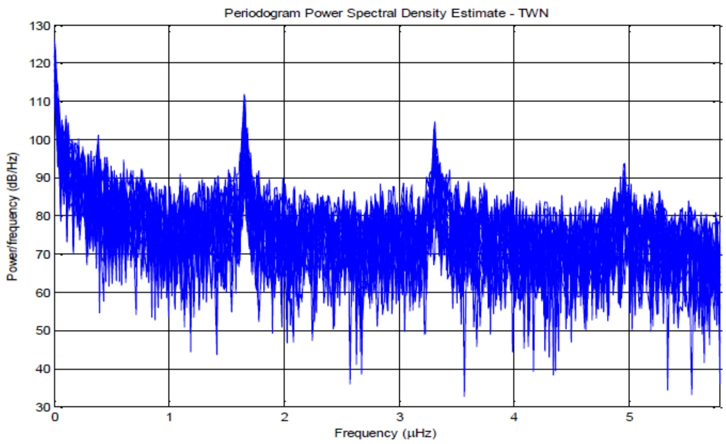


Figure 3.7: Periodogram for TWN Area

Table 3.3: Traffic Data Sample

SDATE	DAILY ERLANG
20040802	101.97
20040803	106.32
20040804	98.7
20040805	105.23
20040806	115.64
...	

In the next section, it is shown that the features extracted from cells that are from similar traffic types are homogeneous. To be able to cluster clearly, there needs to be heterogeneity between cells from different classes and homogeneity between cells from the same class. The following subsection describes the processing chains in achieving this goal.

3.5 Signal Decomposition and Feature Extraction for Traffic Data Sets

In the first phase analysis of signal decomposition and classification, a traditional signal decomposition approach such as the DWPT combined with principal component analysis (PCA) for data reduction is utilised. As discussed previously, the DWPT has been preferred to the DWT for its ability to decompose higher frequency components. This is a clear benefit of the DWPT over the DWT in this application. The PCA approach is used as a data reduction approach to maintain the significant features extracted. This has the potential of dimensionality reduction especially when considering extremely large data sets. Shannon entropy is used as a feature extraction approach. A simple k-means clustering algorithm is then used for classification. This stage determines if distinct clusters are formed based on the features extracted. As described in [66], the DWPT, used as a bank filter and used for feature extraction, is a powerful technique which has been applied with success to many applications. As highlighted above, the original signal is decomposed into a high frequency signal (detail) and a low frequency signal (approximation) in the DWPT approach. The same operation is then applied to the detail and the approximation signals. Each extracted signal contains information of the original signal in the frequency band which has a width of $f_{max}/2^L$, f_{max} being the highest frequency in the spectrum, and L being the number of levels of the decomposition. The steps followed in the feature extraction process is shown in figure 3.8 which yields two coefficients. The steps followed in the processing chain are described below.

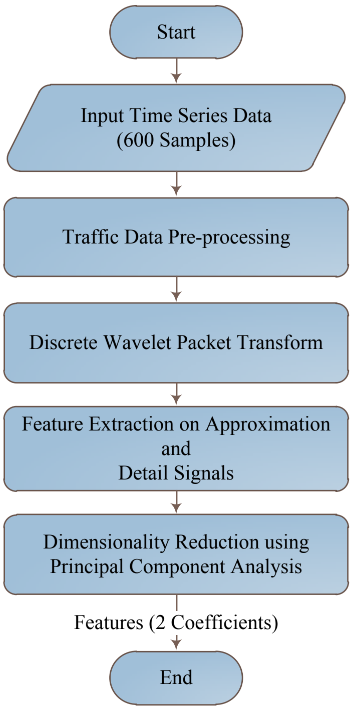


Figure 3.8: Processing Chain of the Traffic Data with Dimensionality Reduction

1. The traffic data pre-processing consists of normalisation of the data. Since the number of users per cell is unknown in our database, the classification of the area according to the mean traffic per user is not possible.

2. The DWPT is then used to separate the frequency patterns, months, weeks, days, etc. A level of decomposition equal to 3 allows the separation of these components.

3. The Shannon entropy is computed on each detail and approximation signal. The Shannon entropy measures the variability of a signal and was chosen as the feature to be extracted. As mentioned in the previous section, the main phenomenon to analyse is the pre-paid/post-paid billing scheme, which expressed by the at spectrum and the peaks experienced. The output at this stage of the processing chain is a vector of 8 coefficients per signal.

4. PCA is then applied to reduce the size of the data. Usually, the first two or three coefficients represent more than 95% of the information. The vectors are then fed into a classification tool.

One can observe that the size of the data to be classified has been reduced from 600 samples to 2 coefficients. This process makes sense only if the initial information that is meaningful is still present in the two coefficients, which is the case in this study. This can be shown through the results obtained through the cluster analysis which is presented in the following section.

Table 3.4: Extracted Coefficients

Coefficient	Information (%)
C1	86.0436
C2	12.8345
C3	0.8056
C4	0.239
C5	0.0389
C6	0.0225
C7	0.0106
C8	0.0052

3.5.1 Cluster Analysis of Extracted Features

Figure 3.9 represents the features extracted from the time series traffic data. Two clusters are clearly visible. The sites were pre-selected to ensure the sites were homogeneous in terms of their behaviour. The sites would constitute a training set for future classification. In the above results, one cluster represents the suburban data, the other the township data. It indicates that the behaviour of the mobile subscriber in the suburbs and township areas are highly homogeneous, and hence, are predictable. The features from the city centre are spread over most of the plane which correspond to the socio-economic diversity inherent to these areas. The classification problem is a 2-class problem. As shown in table 3.4, the first two coefficients represent more than 98% of the complete information. A Bayesian classifier could be used to separate the plane into two distinct regions which would be linear.

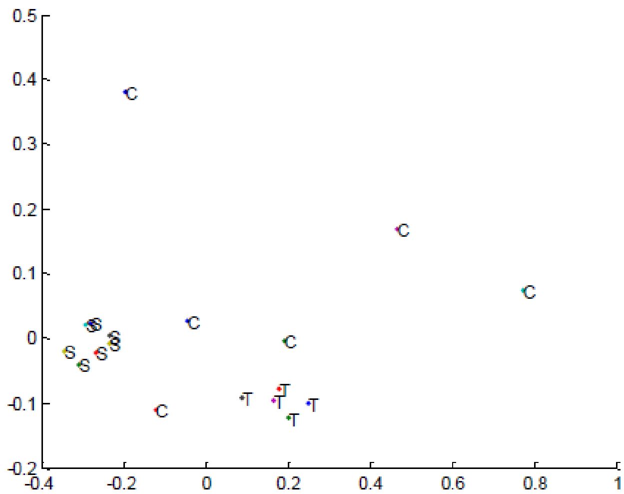


Figure 3.9: Cluster Results based on First Phase Analysis, ($C = CBD, S = Suburb, T = Township$)

As a first conclusion, it is clearly shown that it is possible to classify each site as predominantly suburban area or township area based on the above approach. It is shown that multi-scale analysis in the form of the DWPT is suitable for feature extraction of mobile subscriber classes.

From the presented approach, it is shown that an approach consisting of traditional signal decomposition, feature extraction, and classification approaches can be used to predict the behaviour of subscriber classes. Based on this preliminary conclusion, it is possible to determine traffic patterns based on subscriber classes identified from the feature extraction process. However, a more detailed analysis is required to evaluate the effectiveness of the proposed approach.

3.6 Detailed Analysis of Feature Extraction and Classification Approach

To validate the proposed approach of feature extraction and classification, a second phase modelling and simulation was conducted. The objective of this phase was to test the effectiveness and the validity of clusters generated. As discussed previously, the choice of approaches such as the wavelet transform have been shown to be able to handle signals in short time intervals for high frequency components as well as long time intervals for low frequency components [108]. It was discussed that the use of WMAT approaches have been shown to be useful in denoising multi-dimensional spatial/temporal signals containing steady/unsteady noise [42]. It was also discussed that the EMD approach has been shown to be a powerful tool in analysing composite, nonlinear and non-stationary signals [73]. In addition, the difference histogram approach [109] has been shown to have benefits in terms of computational complexity and its suitability for real-time applications. A variation to the difference histogram developed in this study is also tested and the results evaluated. To further evaluate the effectiveness of the proposed approach, a second data set from a different network provider was used to test the proposed approach in identifying subscriber classes from network traffic data. In the second phase, the extracted features were passed to a Fuzzy C-means (FCM) clustering algorithm to classify the traffic data into distinct traffic classes.

3.6.1 Analysis of the Proposed Subscriber Classification Approach using Selected Feature Extraction Approaches

The proposed approach for subscriber classification consists of two stages: the first stage consists of the signal decomposition and feature extraction process. The signal is first normalised. The normalised signal is then decomposed using the selected approaches. Once the signal decomposition has been achieved, feature extraction is conducted. For each of the feature extraction approaches, the log-energy as discussed previously is selected as the feature to be extracted. Once the feature extraction process has been conducted, the second stage is initiated. In this stage, cluster analysis is conducted on the extracted features. The FCM [9] approach is considered. The FCM approach is selected as an alternative centroid-based clustering approach. In comparison to the k-means approach which was used in the previous case, the FCM approach computes cluster centroids as a weighted mean of all points based on the degree of their belonging to a cluster. The effectiveness of the FCM approach relies on the distance measures computed. Through an iterative approach, cluster centres are moved to the most ideal positions based on the membership of data points considered. The FCM approach may be described as follows: Assume $X = x_1, x_2, \ldots, x_N$ represent a set of unlabeled data points. The FCM approach partitions a data set X into C clusters by minimising the errors in terms of a weighted distance of each point x_i to all the centroids of the identified C clusters [103]. This may be defined as [103]

$$\min j_{FCM} = \sum_{c=1}^{C} \sum_{i=1}^{N} w_{ic}^{p} \|x_i - v_c\|^2 \tag{3.12}$$

subject to

$$\sum_{c=1}^{C} w_{ic}, i = 1, 2, \ldots, N \tag{3.13}$$

The term, $\|x_i - v_c\|^2$ represents the Euclidean distance between each data point and the centroid of a cluster. Algorithm 3 illustrates the steps followed when using the EMD or DWPT approach for feature extraction. When using the difference histogram approach and the modified difference histogram approach, the variation in the feature extraction process is illustrated in algorithm 4. For the DH based approach, the signal is first normalised. The normalised signal is then passed through the difference histogram estimation process. The stability of the DH approach is dependant on the selection of a suitable ε value. The difference histogram bins that are generated are used as features for the clustering process. The following subsections present the results of the feature extraction process for each selected approach.

3.6.2 Analysis Based on the EMD Approach

The EMD approach is applied on the traffic signals extracted from the mobile network to obtain IMFs as discussed in [65]. The EMD toolbox defined in [93] is used to generate IMFs based on input signals considered. The input traffic data consists of

Algorithm 3 Subscriber Classification: $EMD, DWPT$ Approaches

for $n = 1$ to $nSites$ **do**
  Input $tData_n$
  Normalise Data
  Decompose Signal
  Extract $LogEnergy$
end for
for $n = 1$ to $nFeatures$ **do**
  $FCM \leftarrow Features$ {Clustering using FCM}
end for

Algorithm 4 Subscriber Classification: DH Approach

for $n = 1$ to $nSites$ **do**
  Input $tData_n$
  Normalise Data
  Generate Difference Histogram Bins, $dhBins$
end for
for $n = 1$ to $ndhBins$ **do**
  $FCM \leftarrow dhBins$ {Clustering using FCM}
end for

daily traffic measured at the busy hour and represents peak traffic carried per cell per site. The test sample represented a total of 84 different cells. The test sample consisted of a number of CBD, SUB, and TWN sites. From the IMFs generated, log-energy is extracted. A sample of the generated features is shown in table 3.5. The corresponding IMFs generated for the inputted sample is shown in figure 3.10. For the traffic signals inputted, 6 IMFs are generated. The IMF components that are generated are based on the difference between the inputted signal and the mean of the lower and upper envelop value as discussed previously.

Table 3.5: Feature extraction from IMFs generated for CBD, Suburb, and Township

Class	Fea 1	Fea 2	Fea 3	Fea 4	Fea 5	Fea 6
1	-0.0019537	-0.0019183	-0.0032324	-0.0041588	-0.0048448	-0.0047415
2	-0.0024057	-0.0025183	-0.0040728	-0.0047136	-0.00476	-0.0065375
3	-0.0016521	-0.0023932	-0.0036889	-0.0050646	-0.0050691	-0.0050346

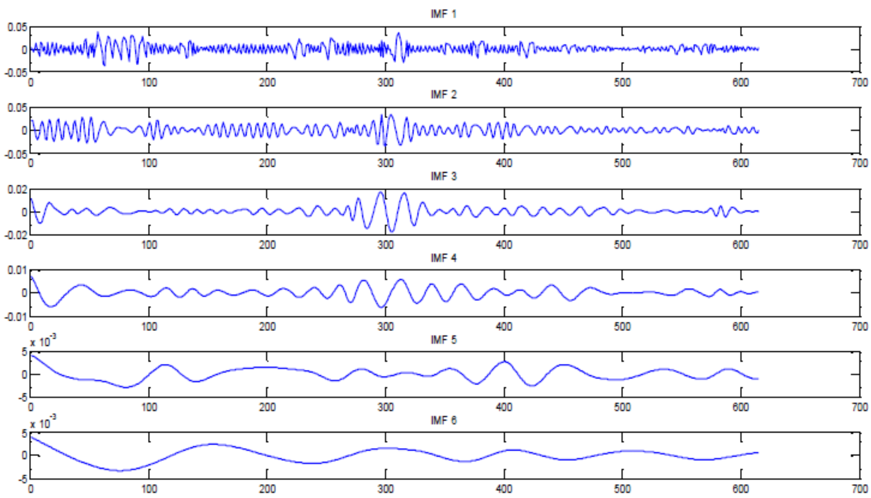


Figure 3.10: Cluster Results based on First Phase Analysis, $(C = CBD, S = Suburb, T = Township)$

3.6.3 Analysis Based on the DWPT Approach

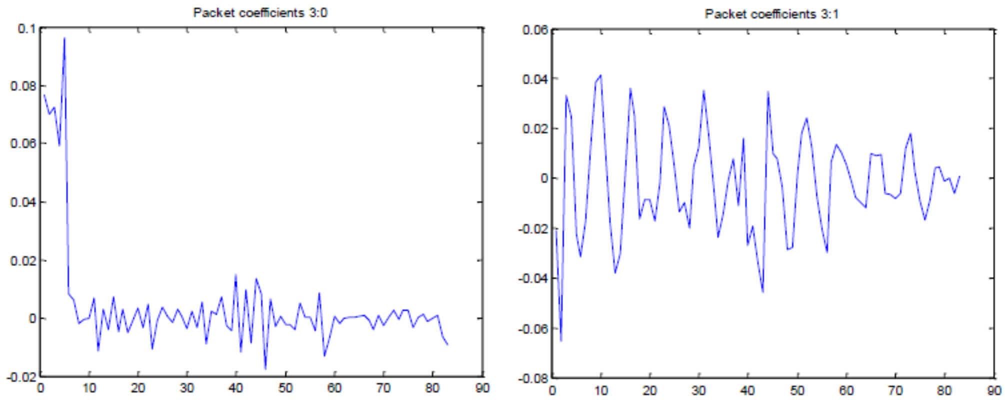
The DWPT approach was applied to the inputted traffic signals. Orthogonal wavelet systems are considered in this study due to their compactness and relationship to multi-resolution filter banks. The daubechies orthogonal wavelet filters were considered ($db1$, $db4$, and $db10$). A decomposition level of 3 was selected. As discussed previously, the suitability of the number of levels is selected to ensure that minimum-entropy decomposition is attained. Various feature extraction techniques were tested including RMS, Shannon-Entropy, and Log-energy (based on 3.2). Based on the analysis, it was found that log-energy provided better results in separating the traffic signals. A sample of the features extracted is shown in table 3.6. The DWPT decomposition of a CBD traffic signal is shown in figure 3.11and figure 3.12. The illustrated decomposition represents detail and approximation of the original inputted signal at level 3. At this level, a total of 8 components are generated at this level (since the level of decomposition was set to 3).

Table 3.6: Feature extraction using DWPT for CBD, Suburb, and Township, level of decomposition set to 3 resulting in 8 features

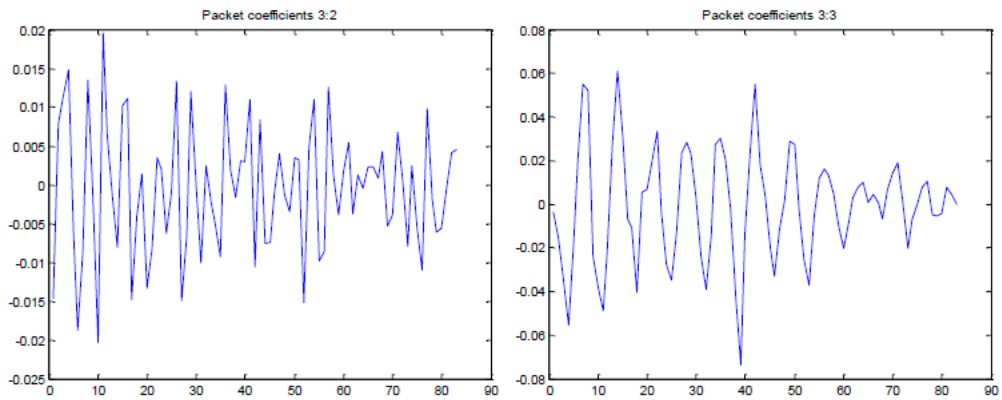
Class	Fea 1	Fea 2	Fea 3	Fea 4
1	-0.00024751	-0.022108	-0.027665	-0.019195
2	-0.00059754	-0.026714	-0.030535	-0.023983
3	-0.0002043	-0.022102	-0.028453	-0.018513
Class	Fea 5	Fea 6	Fea 7	Fea 8
1	-0.02997	-0.029631	-0.022955	-0.03031
2	-0.034781	-0.031434	-0.025231	-0.032659
3	-0.034544	-0.032258	-0.023687	-0.030582

3.6.4 Analysis using the Difference Histogram Approaches

As discussed above, the difference histogram approach proposed in [109] and the adapted version of the difference histogram approach proposed and implemented in this study are considered to extract features from the traffc data. The basic objective of the difference histogram approach proposed in [109] is to determine segments of increase between consecutive segments in a time series based on the ε parameter such that $|x(n+1) - x(n)| \geq |x(n) - x(n-1)| - \varepsilon$. In the second approach, the same condition



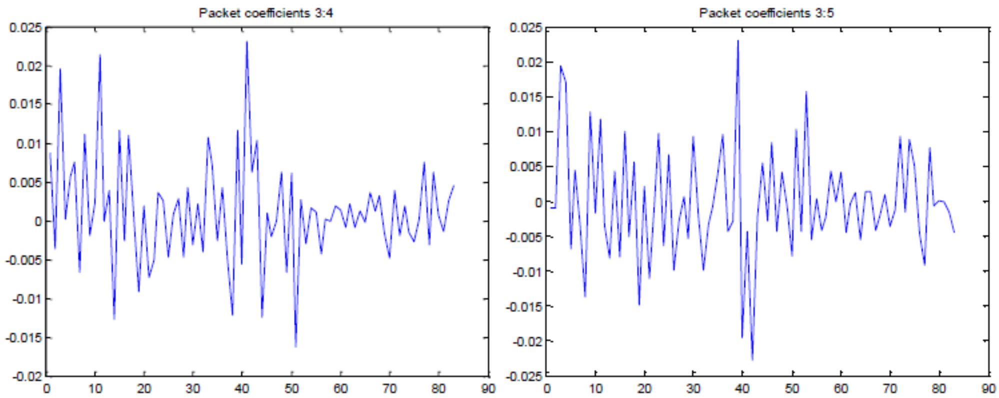
(a) Wavelet Components 3:0 and 3:1



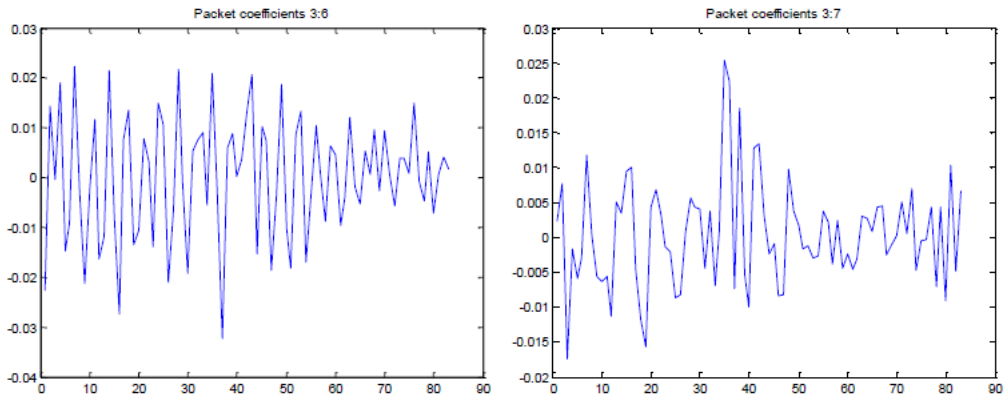
(b) Wavelet Components 3:2 and 3:3

Figure 3.11: Example of DWPT Approximations at Level 3 showing components 0 to 3

is considered. However, the length of segments is considered instead of the frequency of the segments of increase. The mean values of the difference histogram bins obtained for the three different areas considered when using the original difference approach and the modified difference histogram approach is shown in figure 3.13 and figure 3.14 illus-



(a) Wavelet Components 3:4 and 3:5



(b) Wavelet Components 3:6 and 3:7

Figure 3.12: Example of DWPT Approximations at Level 3 showing components 4 to 7

trating the variations obtained for the different traffic classes in the network considered in this study. The variation in the difference histogram bins obtained is clearly visible. From the generated difference histograms, the following conclusions can be made regarding the performance of the difference histogram approach as a potential feature extraction approach for the proposed subscriber classification in mobile networks.

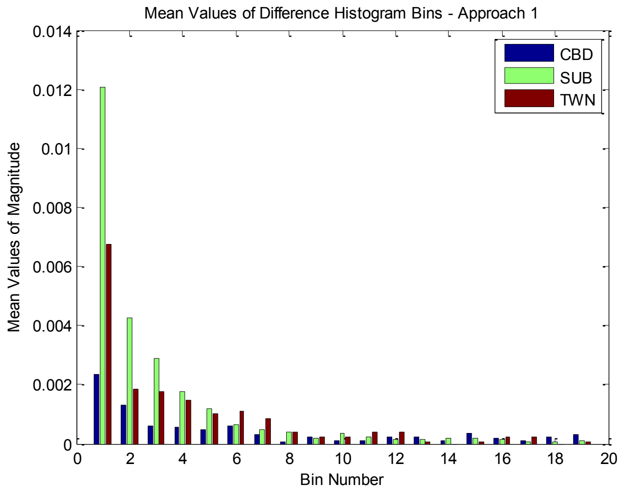


Figure 3.13: Mean Values of Difference Histogram Bins - Approach 1

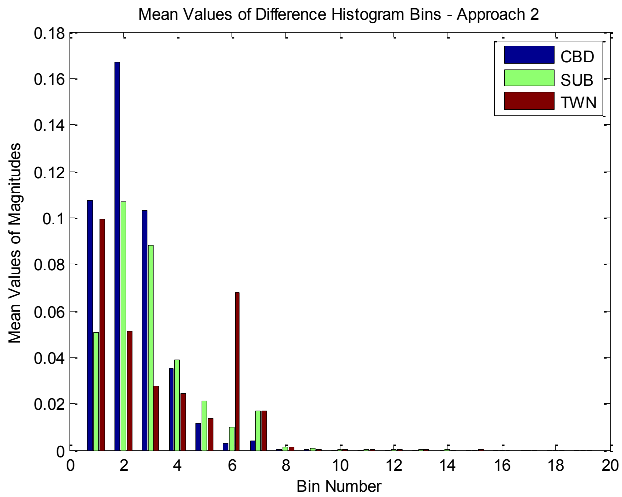


Figure 3.14: Mean Values of Difference Histogram Bins - Approach 2

1. A clear variation in the magnitudes of the difference histogram bins is evident in

the three classes of traffic signals when considering both approaches.

2. The magnitudes of bin numbers of the three classes are quite unique for each class type.

3. The magnitude values are indications of the behavioural patterns which could be connected to each subscriber type in the network.

4. It can be observed that a variation in the magnitudes of the difference histogram bins generated between the two approaches exists. The features extracted are considered as input to the clustering algorithm.

3.7 Cluster Analysis Results

As discussed, for each of the above feature extraction approaches, the FCM algorithm was used to determine whether distinct clusters are formed based on features extracted n each method. The approach was also used to validate the performance of the selected feature extraction approaches. Table 3.7 shows the signals considered.

Table 3.7: Input Data Set

No. of Signals	Signal Type
27	CBD Signals
36	Suburb Signals
21	Township Signals

3.7.1 Cluster Analysis using the EMD Approach

Table 3.8 illustrates the cluster results obtained when using the EMD approach for decomposition. The Class numbers represent one of the three subscriber classes (CBD, SUB, TWN). The interpretations of the results obtained are given below.

1. Of the original 27 CBD signals, 16 were correctly classified, 2 were classified as Suburban, and 9 signals were classified as Township signals.

2. Of the 36 Suburban signals, a reasonably good separation between Suburban and Township signals was obtained with 10 Suburban signals being classified as

Township signals. One signal was mis-classified as CBD. This is indicative of some overlap in the subscriber behaviour between these two regions.

3. Of the 21 Township signals, 4 of the signals were classified as Suburban and 1 as CBD. Again, the potential overlap of signals between Suburban and Township signals is evident.

Table 3.8: Fuzzy C-means results: EMD approach

Class	1	2	3
Class 1:	16	2	9
Class 2:	1	25	10
Class 3:	1	4	16

3.7.2 Cluster Analysis using the DWPT Approach

As discussed above, when using the DWPT approach, various wavelet were tested with the number of levels set to 3 levels for each of the tests. The results obtained when using the DWPT for the wavelet set to $db1$ ($haar$ wavelet) with number of levels set to 3 is shown in table 3.9. Based on the results obtained, the variation in the classification results is evident when using the $db1$ wavelet type for feature extraction.

Table 3.9: Fuzzy C-means results: DWPT approach, Wavelet=$db1$

Class	1	2	3
Class 1:	13	3	11
Class 2:	0	23	13
Class 3:	0	5	16

1. A larger error is seen in the classification of CBD signals with only 13 signals being correctly classified as CBD, 3 as Suburb and 11 signals being classified as Township.

2. A drop in the accuracy of classification of SUB signals is also seen. The number of accurately classified signals was 23 with 13 signals being classified as Township type.

3. When using the $db1$ type wavelet, none of the Township signals were classified as CBD signals. A similar overlap between Township signals and Suburban signals is seen with 16 signals being classified as Township signals and 5 signals being classified as Township signals.

The results obtained for wavelet type set to $db4$ and $db10$ are shown in tables 3.10 and 3.11. This was done to illustrate the variations experienced with varying wavelet types.

Table 3.10: Fuzzy C-means results: DWPT approach, Wavelet=$db4$

Class	1	2	3
Class 1:	16	3	8
Class 2:	0	23	13
Class 3:	0	5	16

Table 3.11: Fuzzy C-means results: DWPT approach, Wavelet=$db10$

Class	1	2	3
Class 1:	16	3	8
Class 2:	0	24	12
Class 3:	0	5	16

From the results obtained, it is evident that very little variation is achieved with the change in the wavelet type. Some improvement is seen in the classification with the variation of the wavelet type, but the improvement is not a marked improvement.

3.7.3 Cluster Analysis using the Difference Histogram Approaches

The final approach considered the two different difference histogram approaches. In the difference histogram approaches, the ε parameter needs to be tuned to improve the performance of features extracted and the extracted bins. This has an influence on the cluster results obtained. To determine the suitability of using the difference histogram approach for feature extraction for subscriber classification, varying ε values where considered for both methods and the results of the classification considered. ε values ranging from 0.01 to 100 were considered. By studying the impact of the variation of the ε values on the accuracy of the cluster results, a suitable ε is selected. The variation in the accuracy of the cluster results obtained for varying ε values is illustrated figure

3.15. Considering the original difference histogram algorithm approach, the cluster results obtained for $\varepsilon = 100$ is shown in table 3.12.

Table 3.12: Fuzzy C-means results: Difference Histogram Approach 1, $\varepsilon = 100$

Class	1	2	3
Class 1:	24	1	2
Class 2:	4	18	14
Class 3:	12	3	6

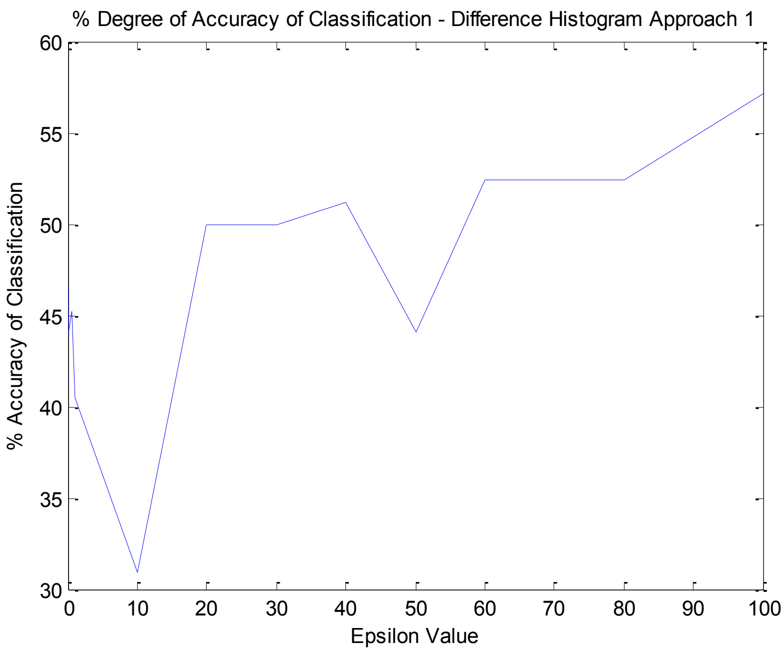


Figure 3.15: Impact of Variation of ε parameter, Difference Histogram Approach 1

From the above, the following conclusions are made:

1. For $\varepsilon = 100$, out of the 27 CBD signals inputted, 24 signals were classified correctly, 1 was classified as SUB and 2 were classified as TWN. A clearer separation between CBD signals and SUB and TWN signals is achieved.

2. Out of the 36 SUB signals, 18 were correctly classified as SUB, 4 were classified as CBD and 14 were classified as TWN. The difference histogram approach showed improvement in the classification, but also exhibited overlap when considering SUB and TWN areas.

3. Out of the 21 TWN signals, only 6 signals were correctly classified as TWN, 3 were classified as SUB and 12 were classified as CBD. For these type of signals, the results showed a drop in the accuracy of the classification.

Considering the modified difference histogram algorithm implemented in this study, the variation in the accuracy of the cluster results obtained for varying ε values is illustrated figure 3.16. The cluster results obtained for $\varepsilon = 30$ is shown in table 3.13.

Table 3.13: Fuzzy C-means results: Difference Histogram Approach 2, $\varepsilon = 30$

Class	1	2	3
Class 1:	24	3	0
Class 2:	5	29	2
Class 3:	0	6	15

From the above, the following conclusions are made:

1. For $\varepsilon = 30$ when considering the second DH approach, out of the 27 CBD signals inputted, 24 signals were classified correctly as CBD signals, 3 signals were classified as Suburban and no signals were classified as Township. A clearer separation between CBD, Suburban, and Township signals is achieved.

2. Out of the 36 SUB signals considered, 29 signals were correctly classified as Suburban signals, 5 signals were classified as CBD, and only 2 were classified as Township type signals. This clearly shows a marked improvement in the classification of the signals when using the second DH approach.

3. Out of the 21 TWN signals, only 15 signals are correctly classified as Township signals and 6 were classified as Suburban signals. A similar result as obtained with the multi-scale approaches can be observed.

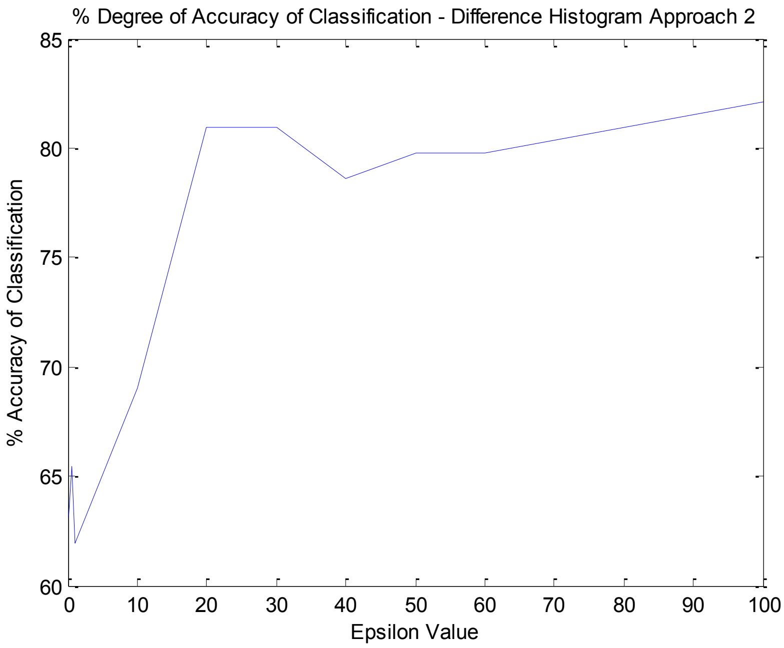


Figure 3.16: Impact of Variation of ε parameter, Difference Histogram Approach 2

The visual representation of the cluster results obtained is shown in figure 3.17. The results represents the 84 signals considered and their association to the clusters identified. The centres of each cluster (representing CBD, SUB, and TWN) are also shown. To test the impact of the cluster results obtained, a second data set was considered and the difference histogram approach (Approach 2) considered for the feature extraction and classification. The objective was to determine if a close association between the cluster centres obtained above could be achieved with the new data set. The result obtained is shown in figure 3.18. A total of 43 cells was considered. The data was obtained from a second network operator in South Africa and represented again the voice traffic carried in a GSM system in a different urban area in South Africa. A close association of the cells to the TWN class cluster centre identified above is seen. This is indicative of the similar subscriber behaviour prevalent in this area.

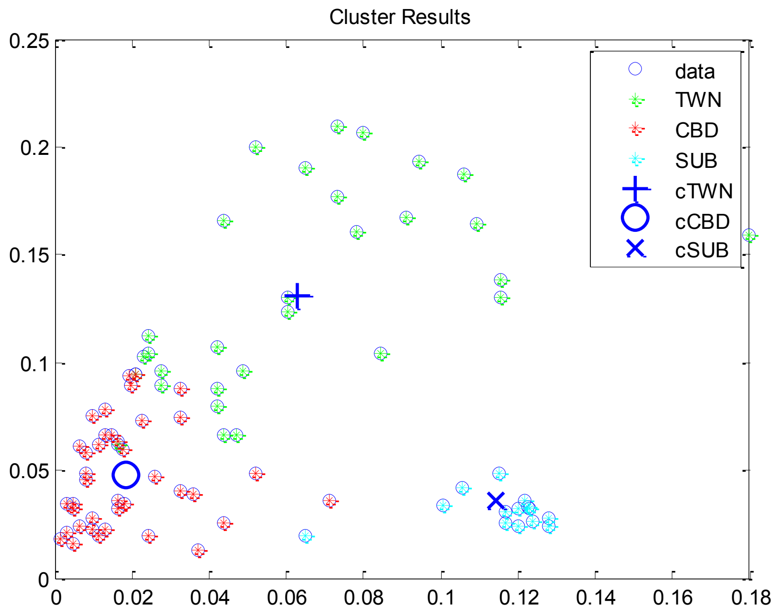


Figure 3.17: Cluster Results: Difference Histogram Approach

3.8 Conclusion

In this chapter, a new approach to subscriber classification in mobile cellular networks was shown that makes use of mobile cellular network traffic as an input. This chapter presented the analysis of the proposed approach in two phases. In the first phase, DWPT, PCA, and a k-means clustering algorithm were utilised to first test the potential of using the proposed approach for feature extraction and classification. The objective was to determine if distinct classes could be formulated using the proposed approach.

In the second phase, a more detailed analysis of the proposed approach for subscriber classification was conducted. The benefit of the proposed classification approach is that it makes use of traditional feature extraction and classification methods to classify subscribers based on mobile network traffic data extracted from the OMC in a mobile

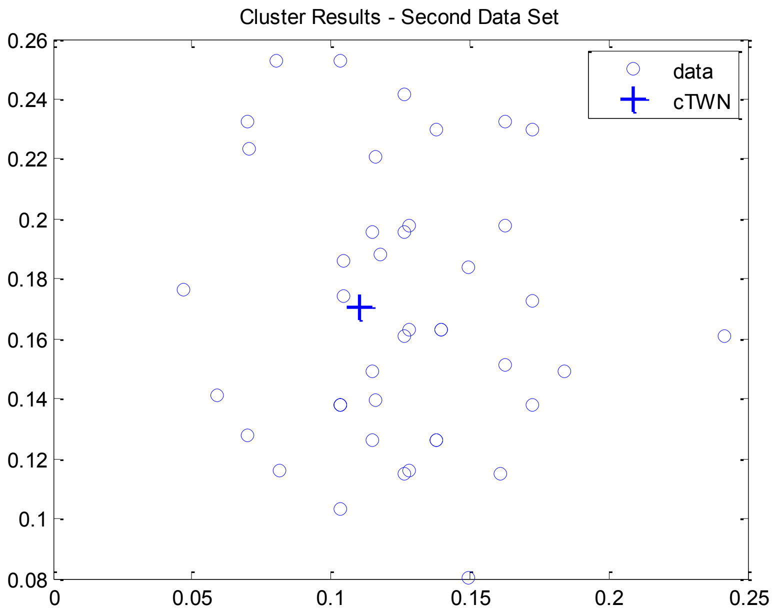


Figure 3.18: Test of DH Approach (Approach 2) on Second Data Set

network. The second phase analysis presented the use of two multi-scale approaches, the difference histogram approach, and a modified version of the difference histogram approach. The impact of the feature extraction approaches on the cluster results obtained were shown. From the analysis, it was shown that the modified difference histogram approach proposed in this study provided better results for the data sets considered. A simple cross-validation approach such as test-sample cross validation could be further implemented to further establish the validity of the clusters obtained.The primary advantage of the proposed subscriber classification approach is the ability of the approach in extracting traffic classes from traffic data by utilising readily available data present in all mobile network providers. The added advantage of the selected approaches is the simplicity of the approaches for feature extraction and segmentation and their ability to handle the non-uniform variations in traffic distributions.

The end goal of the feature extraction approach and subscriber classification is to utilise the obtained subscriber classes for radio resource optimisation in mobile networks. To demonstrate one potential application of the extracted subscriber classes, a novel two-level hybrid channel allocation approach that makes use of a mixed integer linear programming solution is proposed. The proposed approach can be utilised for network resource optimisation based on identified subscriber classes. The next chapter presents a proposed hybrid channel allocation approach that takes into account the varying subscriber classes identified in this chapter.

Chapter 4

A Two-Level Hybrid Channel Allocation Approach for Mobile Cellular Networks

4.1 Introduction

Based on the subscriber classification approach presented in the previous chapter, the second part of this study considers the proposal of a novel channel allocation model suited to the traffic variations experienced in the area under study. A preliminary background to the problem is first provided followed by an overview of optimisation solution approaches for the problem. The problem is then modelled using a selected optimisation approach which is presented. This is followed by results obtained and a summary of the results.

4.2 Background of the Problem

The network optimisation strategy employed in a mobile cellular network begins with the initial network provisioning stage that considers approaches to improve the allocation of available resources as discussed in Appendix B. The optimisation of resources during the network planning stage takes into consideration the capacity and coverage planning and frequency optimisation from a network roll-out point of view. As highlighted previously, as a mobile cellular network begins to mature, the need to optimise the network from a channel allocation point of view needs to be considered. The solution to the resource allocation problem in a mobile cellular network may be considered to be a combinatorial optimisation problem. As discussed in Appendix A, various approaches have been proposed for the channel allocation problem to meet capacity constraints in a network. The optimisation of frequencies impacts on the operational expenditure of the network (OPEX) as it delays the need to acquire frequencies in the network. It also contributes to the improvement of the GOS in the network. Various channel allocation approaches may be implemented in the network consisting of fixed, dynamic or hybrid approaches. Depending on the maturity of a network, a simplistic fixed channel allocation approach may be sufficient. However, as the network matures, a dynamic channel allocation strategy could alleviate the inefficiencies of a purely fixed channel allocation approach that requires constant human intervention to effect capacity changes in the network. However, the migration to purely dynamic approaches also has its drawbacks when considering the complexity and the overheads generated when conducting dynamic frequency allocation.

An alternative to the above is to consider hybrid channel allocation schemes. Based on the subscriber classification conducted in the previous chapters, the objective of the approach proposed in this study is to consider a hybrid channel allocation scheme that takes into account the varying subscriber traffic demands in the network. Since the traffic demands are time dependant, an interval-based hybrid channel allocation that allocates resources during busy periods and releases them to the available pool of channels when not busy is proposed. Based on this, two-levels of channel allocations are proposed. For each cell, a fixed allocation of channels is considered which takes into account a maximum threshold of traffic that needs to be carried per cell. Figure 4.1 illustrates the traffic carried in all cells considered in the traffic class CBD. The traffic represents the variation of maximum to minimum traffic carried in various cells in a CBD type area. A maximum threshold for the fixed channel allocation can be identified from the figure as shown. A similar presentation of the traffic carried in SUB type cells is shown in figure 4.2. To cater for variations that exceed the maximum thresholds experienced in the cells, a dynamic pool of channels is considered to take into account the variations. Unlike traditional dynamic channel allocation approaches which take into account allocating a either a global pool of channels for dynamic channels or the hybrid approach which considers fixed pools of fixed/dynamic channels, the proposed approach in this study considers adapting the dynamic channel allocation of channels through a re-allocation approach in pre-defined periodic intervals.

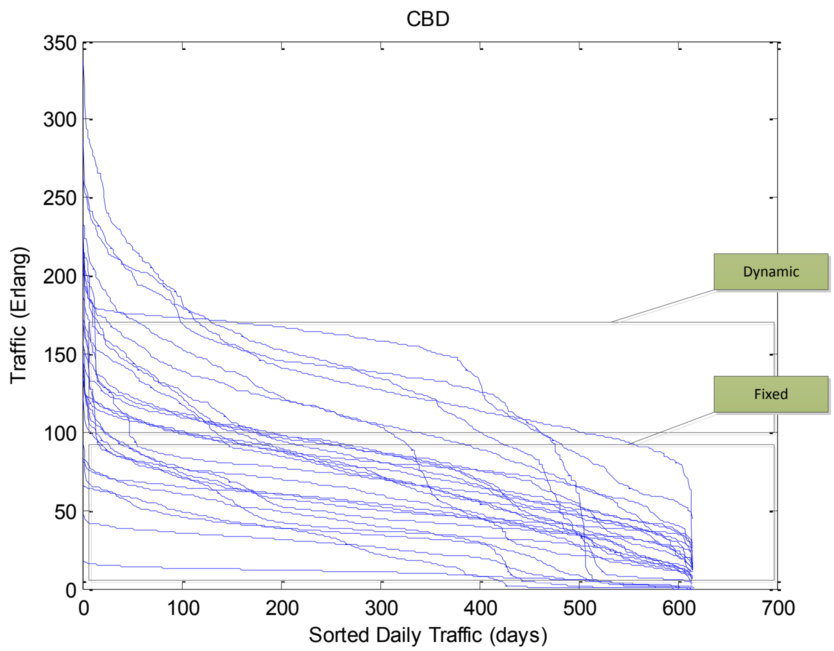


Figure 4.1: Sorted Traffic Distribution, CBD Region in Area Under Study with Proposed Hybrid Channel Allocation Scheme

The number of periods selected for re-allocation can be predetermined based on the frequency of busy periods experienced in cells or in the average traffic variations experienced for each traffic classes identified in the traffic classification process. Figure 4.3 illustrates this concept. In the above figure, different time periods are defined during which channel re-allocation needs to take place. Depending on the traffic class, the number of periods defined may vary which is linked to the traffic variations experienced in the traffic class. The above process defines two levels of adaptation of capacity to meet varying traffic demand in the network. The above two combinations of channel allocation that considers the fixed thresholds and the period-based dynamic re-allocation of channels is referred to as the $two - level\ hybrid\ channel\ allocation$

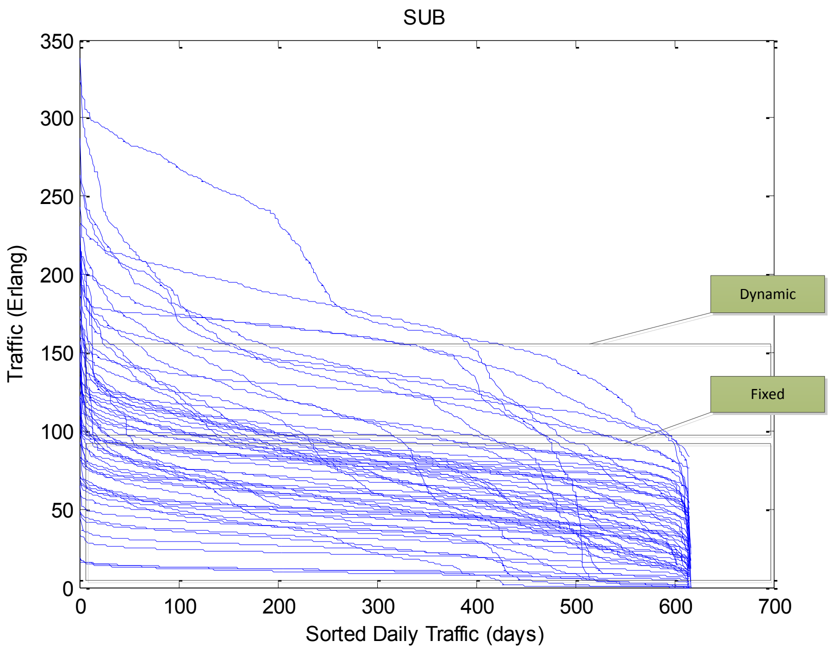


Figure 4.2: Sorted Traffic Distribution, SUB Region in Area Under Study with Proposed Hybrid Channel Allocation Scheme

scheme in this study. A summary of the proposed two-level hybrid frequency allocation approach is shown in figure 4.4. The proposed approach consists of two stages. The first stage consists of a traditional fixed channel allocation. This stage allocates the fixed capacity per base station in the network. To adapt to the varying capacity demand in the network according to traffic classes, the period-based dynamic channel allocation is conducted to allocate channels to cater for the variations in the traffic demand experienced in each traffic class. As discussed in [78], the channel allocation problem may be considered as a facility location problem and may be solved using combinatorial optimisation solvers. Before presenting the proposed channel allocation model, a background on solving combinatorial optimisation problems is first presented.

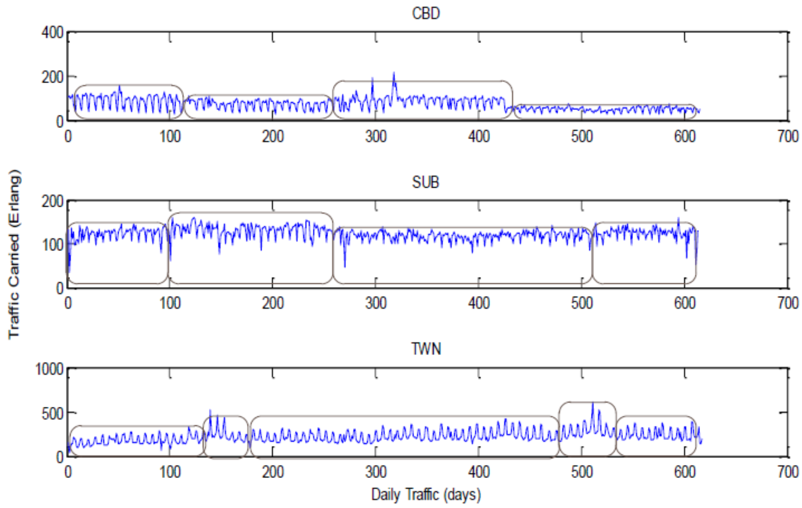


Figure 4.3: Definition of Traffic Periods during which Allocated Channels are Re-optimised

4.3 Solving Combinatorial Optimisation Problems

As highlighted in Chapter 2, the objective of a combinatorial optimisation problem (COP) is to determine values for discrete variables such that an optimal solution with respect to an objective function is identified subject to problem specific constraints[90]. In the domain of management science, which is considered synonymous with operational research, one of the branches considered takes into account the optimum allocation of limited resources across competing activities under a set of constraints imposed by the nature of the problem being studied [8]. The constraints considered take into account various factors that influence the problem studied such as financial aspects, technological aspects, organisational aspects etc. [8]. COP problems are considered to be NP-Hard [90] requiring the use of combinatorial optimisation solvers. Due to the importance and applicability of COP in business and management environments, a number of approaches have been proposed for the solving of such problems including mathematical or exact approaches, meta-heuristic approaches which include bio-inspired approaches, and machine learning approaches. As stated previously, the allocation of channels to

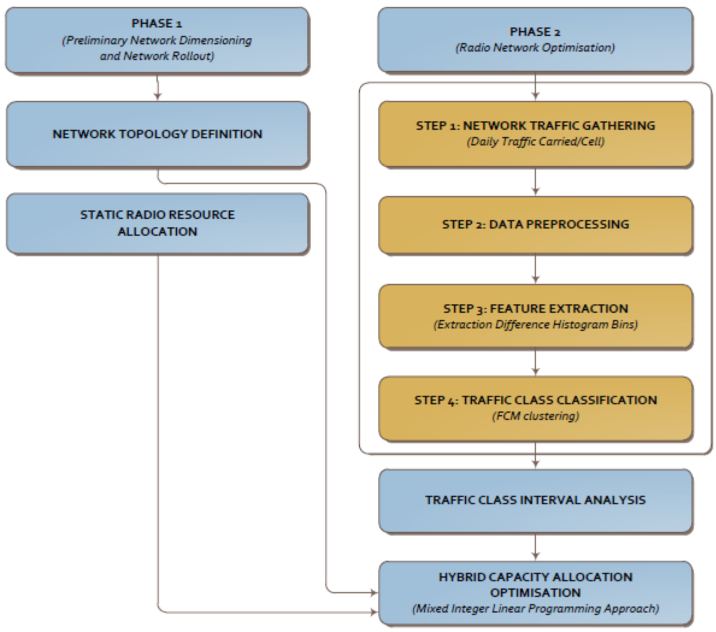


Figure 4.4: A Proposed Two-Level Hybrid Channel Allocation Approach

BTS can be considered to be a facility location problem. This problem can be solved using integer linear programming approaches belonging to the family of mathematical programming approaches.

Mathematical programming approaches, or exact approaches, are techniques that are guaranteed to find an optimal solution [90]. However, with an increase in problem size, the computational time of such approaches can be highly compromised. In such scenarios, the use of heuristic approaches are recommended [90] which compromise on attaining an optimal solution and considering a near-optimal solution within a limited amount of time. Table 4.1 [90] provides a listing of exact approaches and the broad meta-heuristic approaches. The use of meta-heuristic based approaches in solving the base-station placement problem is highlighted through various studies that have been conducted on 2G and 3G based networks. An overview of these studies is presented in

Appendix B.

Table 4.1: Exact and Meta-Heuristic Solvers for Optimisation Problems

Exact Approaches	Meta-Heuristic Approaches
Branch and Bound	Simulated Annealing
Dynamic Programming	Tabu Search
Constraint Programming	Iterated Local Search
(Integer Linear Programming (ILP))	Variable Neighbourhood Search
Cutting plane and column generation	Population-based (Genetic Algorithms,
Branch and Cut	Particle Swarm Optimisation)
Branch and Price	Scatter Search
	Estimation of Distribution (Ant Colony)

As discussed in [8], optimisation models can be classified based on the number of periods considered (static (single time period) or multi-stage (multiple time periods)). The optimisation model can be classified based on the behaviour of the parameters considered in the optimisation model. The optimisation model is considered to be deterministic or stochastic depending on whether the parameters in the model are known constants or uncertain with probabilistic values [8]. The optimisation model can be considered to be parametric if some of the parameters of the model are allowed to vary systematically [8]. Optimisation models can be further classified based on the behaviour of variables in the optimal solution.

If there are no limitations on the values of the variables for constraints considered, the optimisation model is considered to be continuous. However, if the variables can only assume discrete values, then the optimisation model is considered to be discrete or integer [8]. The family of integer linear programming (ILP) models fall within this category. In some instances, when the problem considers some variables that are integer and others as continuous, the optimisation problem is considered to be a mixed integer problem [8]. The family of mixed integer linear programming (MILP) falls within this category.

4.4 The Mathematical Programming Approach for Solving Linear Problems

Mathematical programming can be defined as a representation that obtains the best possible allocation of scarce resources. A linear programming model is a mathematical representation that uses linear functions exclusively [8].

4.4.1 Representation of a Linear Programming Model

In mathematical terms, a linear programming model can be expressed as the maximisation (or minimisation) of an objective function subject to a given set of linear constraint(s) [8]. This may be represented as follows [8]:

Consider a set of n decision variables $x_1, x_2, \ldots, x_n$. The linear programming problem considers finding the set of decision variables that satisfy the maximisation (minimisation) of an objective function, z, given by:

$$z = \sum_{j=1}^{n} c_j x_j \tag{4.1}$$

The above is subject to the following constraints:

$$\sum_{i=1,j=1}^{m,n} a_{ij} x_j \leq b_i \tag{4.2}$$

The following constraint is also usually considered [8]:

$$x_j \geq 0, \forall j = 1 \ldots n \tag{4.3}$$

$$x_j \text{ is integer for all } j = 1 \ldots n \tag{4.4}$$

In the above, the terms, c_j, a_{ij}, and b_i are constants. If a solution can be found in which the decision variables $x_i, i = 1 \ldots n$ meet the constraints simultaneously, a feasible solution to the linear programming problem is said to be found. A feasible solution that optimises the objective function is referred to as an optimal feasible solution [8]. When additional constraints are added in which some of the decision variables, $x_j, j = 1 \ldots n$ are integer variables, the problem is said to be an integer linear programming (ILP) problem. As stated, if some of the integer variables are real and others are integer, the problem is referred to as a mixed-integer linear problem (MILP).

4.4.2 The Capacitated Facility Location Problem

When considering the base station problem and the capacity allocation problem, one of the objectives of the problem is to determine the most optimum locations of base station sites to meet the required demand of subscribers. This may be modelled as a Capacitated Facility Location Problem which is discussed here. Many economical decision problems focus on the selection and/or placing of certain facilities (or resources) to serve given demands efficiently [112]. In the domain of ILP problems, discrete facility location problems focus on determining best locations of facilities to meet demands of users. A generalised version of the above is the universal facility location problem (UniFL) in which the cost of opening each facility is an arbitrary function of the amount of demand served by it [75]. The UNiFL problem is also referred to as the capacitated facility location problem. The objective of these problems is to decide where facilities need to be located within a finite set of sites taking into account the needs of clients that need to be served while optimising certain economic criteria [14].

The problem may be formulated as follows [14]: Consider I and J are two sets representing N clients and M facilities respectively. Consider that the following variable is defined:

$$y_i = \begin{cases} 1 & \text{if facility } i \text{ is open} \\ 0 & \text{otherwise} \end{cases} \tag{4.5}$$

Consider that the following constraints are defined [112]: For the above problem, each client's demand must be satisfied and is defined by

$$\sum_{i \in I} x_{ij} = d_j, \forall j \in J, \tag{4.6}$$

where d_j represents the demand of the j^{th} client. Each client cannot be served from facility i unless a facility is placed at i. This is defined as

$$\sum_{j \in J} x_{ij} \leq u_i y_i, \forall i \in I, \tag{4.7}$$

where u_i represents the capacity of facility i. The function to be optimised is given by

$$\max Z = \sum_{i \in I} f_i y_i + \sum_{i \in I} \sum_{j \in J} c_{ij} x_{ij}, \tag{4.8}$$

where c_{ij} is the cost for shipping each unit of demand from facility i to client j and f_i is the fixed cost of opening a facility placed at i [14].

4.4.3 Facility Location Problem with Incremental Costs

A special case of the facility location problem is the facility location problem with incremental costs which is also known as the linear-cost facility location problem [75, 112]. The facility cost takes into account an additional cost per unit demand served as follows [75, 112]:

$$f_i(y) = \overline{f_i}.\,[y > 0] + \sigma_i.\,y, \tag{4.9}$$

where σ_i represents the additional cost per unit demand served.

4.5 Solving Mixed-Integer Linear Problems

Dantzig developed the simplex method for solving general linear-programming problems in 1947 [8]. The ease of implementation and the growth in powerful computing platforms made this approach widely adopted in many fields of application. While the simplex method has been shown to be an effective approach in solving linear programming problems, in the case of mixed-integer programming problems, a number of techniques have been developed without a specific technique being a dominant technique. In solving a linear optimisation problem, due to the convexity of feasible region, any locally optimal solution would be a global optimum. The general strategy of finding a solution to a MILP is to generate recursively partial descriptions of a set S containing one or more optimal solutions [122]. The methods employed for solving the above may be classified into broad categories namely [8, 122]:

1. Enumeration techniques which focus on enumerating all the finitely possible solutions;
2. The cutting-plane approaches which focus on the relaxation of integrality restrictions and solving the resulting LP.
3. Group-theoretic approaches.

4.5.1 The Branch-and-Bound Approach

Enumerative algorithms are considered amongst the simplest approaches for solving ILP. One of the most commonly used enumerative approaches is the *branch* and *bound* approach [122]. The approach is basically a *divide*-and-*conquer* approach in which the feasible region is sub-divided into manageable sub-divisions [8]. Variants of the technique are used by practically all state-of-the-art solvers [122]. For example, the commercial solver, CPLEX which is considered in this study, makes use of this technique. The branch-and-bound algorithm may be described as follows. Consider a linear problem LP defined as:

$$\begin{aligned} \min z &= c^t x \\ Ax &\leq b \\ x &\geq 0 \end{aligned} \tag{4.10}$$

The initial relaxation of LP, defined as LP_0 is then considered. If the solution of LP_0 is integral, then an optimal solution is reached. Otherwise, a choice is made on relaxation of LP by considering lower or upper non-integer values for x through a branching step and evaluating the objective function. If the solution reached is less than the best integer found (the incumbent), a fathom or pruning operation takes place and the node is bound. This iterative process is continued till the best integer is determined. A summary of the above algorithm is illustrated in algorithm 5.

4.5.2 Relaxation and Duality

According to Linear Programming (LP) theory, a dual problem can be associated to each LP. The dual of the dual LP is the primal LP. The dual problem provides an upper bound for the optimal value of the primal problem. The relationship between the primal problem and its dual are referred to as weak and strong duality theorems and are defined as [90]:

1. The value of every finite feasible solution to the dual problem is a lower bound for the primal problem. The finite feasible solution of the primal problem is an upper bound for the dual problem. Hence, if the dual problem is unbounded, then the primal is infeasible and vise versa.

Algorithm 5 Branch-and-Bound Algorithm

```
Initialise Problem
Use a Sub-Optimal Heuristic Method to Search for an Initial Incumbent
if Solution Found then
  Exit
else
  Set z̄ = ∞ {Initial Cost}
end if
Solve LP_0
if Solution is Integral then
  Exit
else
  Chose a Non-Integer Variable and a Branching Step
end if
while Tree is not Empty do
  Chose node_i
  Solve LP_i
  if z_i ≥ z̄ then
    Prune Node
  else if Solution is Integral then
    z̄ = z_i
  else
    Branch
  end if
end while
```

2. If the primal problem has a finite optimal solution given by z^*_{LP}, then the dual has the same solution w^*_{LP} and vice versa.

In the case of a ILP, a *weak* dual is any maximisation problem w such that $w(u) \leq cx$, $\forall x \in \{Ax \geq b, x \geq 0, x \in \mathbb{Z}^n\}$ [90] where

$$\max w = w(u), u \in S_D \tag{4.11}$$

In the above equation, u is considered as the a feasible solution of the dual LP and is considered to be in S_D, which represents the set of possible optimal solutions in the dual LP. The *strong* dual theorem states that if there exists a primal optimal solution x^*, then the dual has an optimal solution u^* such that $w(u^*) = cx^*$. Weak duals are iteratively strengthened during the optimisation process for solving an ILP problem[90].

An important concept in integer programming is the use of relaxations in which some or all constraints of the problem are loosened or omitted [90]. Relaxations are mostly used to obtain related, simpler problems which can be solved efficiently yielding bounds and approximate solutions for the original solution [90]. The linear programming relaxation of a ILP is obtained by relaxing the integrality constraints of the ILP. A standard relaxation technique for ILP problems which yields tighter bounds than the LP relaxation is the Lagrangian Relaxation. The Lagrangian relaxation considers the penalising of the original subset of constraints and is sometimes referred to as the *complicating* constraints. A Lagrangian relaxation is created by removing (relaxing) a set of constraints by weighting them with Lagrangian multipliers and placing them in the objective function [71]. The objective is to obtain a relaxed problem which is easier to solve than the original problem. Consider the following ILP [90]:

$$\begin{aligned} \min z = c^t x \\ Ax \geq b \\ Dx \geq d \\ x \geq 0, x \in \mathbb{Z}^n \end{aligned} \tag{4.12}$$

When considering the Lagrangian relaxation, the constraint $Dx \geq d$ is replaced by additional terms in the objective function as given in [90]:

$$\min z_{LR}(\lambda) = c^t x + \lambda(d - Dx) \tag{4.13}$$
$$Ax \geq b$$
$$x \geq 0, x \in Z^n$$

For any $\lambda \geq 0$, $z_{LR}(\lambda) \leq z$. D in the above represents the subset of constraints that relaxed or penalised as described above.

4.5.3 Lagrangian Relaxation in Capacitated Facility Location Problems

In the relaxation of the Capacitated Facility Location Problem(CFLP), the Lagrangian sub-problem may be defined by associating non-negative Lagrangian multipliers, λ_i, with the constraints defined in Equation (4.7) and incorporating them into the objective function which would give the following expression [71]:

$$\min \sum_{i=1}^{N} f_i y_i + \sum_{i=1}^{N} \sum_{j=1}^{M} (c_{ij} + \lambda_i a_j) x_{ij} - \sum_{i=1}^{N} \lambda_i b_i \tag{4.14}$$

Through an iterative procedure, the multipliers can be updated between successive solutions of the uncapacitated sub-problems.

4.6 Formulation of the Two-Level Hybrid Channel Allocation Approach

The channel allocation or assignment problem is considered as the allocation of frequencies such that the required network capacity is maximised. The mixed-integer linear programming approach proposed by Mazzini in [78] is used as the basis for the proposed approach in this study. However, only the BTS and the basic channel allocation model considered by Mazzini is taken into account. The impact of backbone networks on the site placement problem is not taken into account as the focus in this study is primarily on the channel allocation aspect. The problem may be considered as a capacitated facility location problem based on the idea that base station sites are considered as facilities that need to provide resources to users based on demand for the resources. Each facility i is considered to provide a service to user j taking into account the demand (d_{ij}) at facility i (BTS in this case) and the demand of the user. In the formulation of the objective function, the following sets are considered:

I is the set of all base station sites in the network (BTSs).
J represents the set of all squares which are used to indicate the geographical areas that are covered by BTSs in the network.
K represents the set of all frequency channels available in the network.
N_i is a set that is used to represent the BTSs that interfere with BTS_i.
T represents a set of Periods considered in the hybrid channel allocation model considered in this study.

Based on the above sets, the following objective function is formulated for the hybrid channel allocation model considered in this study considered as a minimisation problem that considers the minimisation of the allocated number of frequencies.

$$\min z = \sum_{i \in I} f_i y_i + \alpha \sum_{i \in I, j \in J} \delta_{ij} x_{ij} + \sum_{i \in I} \beta_i \sum_{k \in K} \sum_{t \in T} \delta_{ikt} + \sum_{i \in I} \sum_{t \in T} \sum_{k \in K} \gamma_k z_{ikt} \tag{4.15}$$

In the modelling of the objective function, the following constants are considered:

m_i represents the maximum number of squares that are covered by BTS_i.
η_i represents the maximum number of frequency channels that are assigned to BTS_i
d_j represents the demand for frequency channels that is generated in square j.
f_1 is the minimum frequency distance between adjacent frequency channels. This distance is defined to ensure that adjacent frequency interference is minimised during the frequency allocation.

A number of variables are also considered for the modelling of the problem considered. The following variable is used to indicate if BTS_i covers square j.

$$b_{ij} = \begin{cases} 1 & \text{if } BTS_i \text{ covers square } j \\ 0 & \text{otherwise} \end{cases} \tag{4.16}$$

The following variable determines if BTS_i is selected or not.

$$y_{ij} = \begin{cases} 1 & \text{if } BTS_i \text{ is selected} \\ 0 & \text{otherwise} \end{cases} \tag{4.17}$$

The following variable determines if frequency channel k is assigned to BTS_i during period t.

$$z_{ikt} = \begin{cases} 1 & \text{if frequency channel } k \text{ is assigned to } BTS_i \text{ during period } t \\ 0 & \text{otherwise} \end{cases} \tag{4.18}$$

Variable Δ_{ij} is used to determine the euclidean distance between BTS_i and square j. To represent the extent of coverage BTS_i provides to square j, variable x_{ij} is used. The value of x_{ij} ranges between 0 and 1 and is represented as

$$0 \leq x_{ij} \leq 1 \tag{4.19}$$

In the formulation of the objective function to solve the optimisation problem, the cost of installing BTS_i at a location (based on Mazzini's formulation). The following new considerations are made as an extension to Mazzini's work:

1. A new constraint is placed to limit coverage of BTS_i to a served area.
2. A cost of allocating a frequency k in period t is added to adapt the channel allocation to consider re-allocation during different periods.
3. An additional cost is added to the frequency allocation per period in an exponential manner through which added cost is incurred with increase in frequencies requested.

In the formulation of the objective function, the following cost functions are defined:

1. f_i is the cost associated with the installation of BTS_i.
2. α is a weighting factor that can be adapted to affect the cost associated to the distance between a serving BTS_i and square j.
3. β_i is a weighting factor that can be adapted to influence the cost associated to allocation of a frequency channel to a BTS_i.
4. δ_{ikt} is defined as the cost associated to the allocation of frequency k in period t based on variable $zikt$ such that

$$\delta_{ikt} \geq z_{ikt} - zik(t-1), \tag{4.20}$$

The cost expression 4.20 may be further described as follows:

1. For $z_{ikt} = z_{ik(t-1)} = 1$, $\delta_{ikt} = 0$ implying that if a channel was allocated in period $(t-1)$ and allocated at period t implying a frequency channel previously allocated that needs to be reallocated, no cost is incurred.

2. For $z_{ikt} = 1$, $z_{ik(t-1)} = 0$, $\delta_{ikt} = 1$ which implies that a cost is incurred if a frequency that was not allocated in period $(t-1)$ is allocated is allocated in period t.

3. For $z_{ikt} = 0$, $z_{ik(t-1)} = 1$, would give a negative cost. However, according to 4.20, $\delta_{ikt} \geq 0$ which implies that $\delta_{ikt} = 0$. As a result, the cost incurred would be 0.

An additional marginal increase in cost, γ_k, is associated to the cost of frequency allocation at BTS_i for channel k in period t. The cost increases with increase in the frequency number. In this study, a simple exponential function such a $\gamma_k = e^{k\sigma}$, where σ can be varied to increase the extent of cost applied to the frequency allocation.

In developing an objective function for the problem considered, the following constraints are considered. The first two constraints relate to the maximum coverage of BTS_i and the maximum squares it can cover respectively.

$$\sum_{i \in I} b_{ij} x_{ij} \geq 1, \forall j \in J \tag{4.21}$$

$$\sum_{j \in J} b_{ij} x_{ij} \leq m_i y_i, \forall i \in I \tag{4.22}$$

The following constraint ensures that the minimum frequency distance is maintained between allocated channels to avoid interference with only one channel being allocated from a frequency set at a distance of f_1.

$$\sum_{k=1}^{l+f1} z_{ikt} \leq 1, \forall i \in I, l = 1, \ldots, |k| - f_1, \forall t \in T \tag{4.23}$$

To ensure that the frequency allocation ensures that interfering BTSs are not considered in the allocation of z_{ikt}, the following constraint is defined:

$$z_{ikt} + \sum_{l \in N_i} z_{lkt} \leq 1, \forall i \in I, \forall k \in K, \forall t \in T \tag{4.24}$$

The following constraint is defined to ensure that the allocated channels exceeds the demand at BTS_i.

$$\sum_{k \in K} z_{ikt} \geq \sum_{j \in J} d_j x_{ij}, \forall t \in T \tag{4.25}$$

The following constraint is defined to ensure that the frequency channels that are allocated to BTS_i is less than the maximum allowable frequencies that can be allocated to a BTS.

$$\sum_{k \in K} z_{ikt} \leq \eta_i y_i, \forall t \in T \tag{4.26}$$

4.7 Simulation and Performance Evaluation

CPLEX offers C, C++, Java, .NET, and Python libraries that solve linear programming (LP) and related problems [45]. Of particular interest is CPLEX's tools for solving mathematical programming problems in which some or all of the variables must assume integer values in the solution. In CPLEX, the optimising of a Mixed Integer Programming model involves the following [45]:

1. Finding a succession of improving integer feasible solutions (solutions that satisfy linear and quadratic constraints and integrality conditions)

2. Working towards the proof that no better feasible solution exists and is undiscovered as highlighted in the branch-and-bound algorithm. CPLEX terminates the MIP optimisation in a number of circumstances. One of the conditions that the solver terminates is when CPLEX declares integer optimality and terminates when it finds an integer solution and all parts of the search space have been processed.

MATLAB Version 7.12.0.635 (R2011a) [77] was used to formulate the constraints and to model the channel allocation problem based on the above formulation. MATLAB is used to generate a Mathematical Programming System (MPS) matrix string containing the mixed integer linear programming problem. The MPS file is then inputted to IBM ILOG CPLEX Optimization Studio version 12.2 [46] to solve the MILP problem. On obtaining a feasible solution, a solution file is generated in CPLEX which is read back into MATLAB and the solution displayed. The simulation was run on a HP Pavillion dm3 laptop with a 1.3GHz U1400 processor with 4GB of RAM. The laptop runs a 64bit Windows 7 operating system. A summary of the approach followed is shown in figure 4.5. The basic parameters considered for the simulation together with typical values used are shown in table 4.2. Varying values for the parameters were considered. The values shown below were considered taking into account total execution time for the simulations which are related to the parameter values, and subsequently, the number of variables in the problem. With increasing values, the number of variables increases exponentially and hence impacts on the total execution time. Two sets of simulations were considered. The first simulation considered the channel allocation problem that considers the first three cost functions defined in the objective function 4.15. This includes the cost of placing BTS_i at square j, the cost associated to distance between BTS_i and square j, and the cost associated to allocation of frequency k in period t.

Table 4.2: Exact and Meta-Heuristic Solvers for Optimisation Problems

Parameter	Parameter	Description Value
Nbts	Number of BTSs	18
Ns	Number of Squares	100
K	Number of Frequency Channels	100
Np	Number of Periods	4

The second simulation considered the additional fourth cost term given in the objective function which associates a cost to frequency allocation with increase in the frequency number. This adds added cost to frequency allocation with increased frequency allocation requests.

4.7.1 First Scenario: Fixed Channel Cost per Frequency

Figure 4.6 illustrates the CPLEX initialisation for the first scenario.

The corresponding termination reached on finding an optimal solution is shown in figure 4.7. The summary of the performance of the CPLEX solver for the first scenario is given in table 4.3. The solution takes into account the demand (represented as squares) and coverage per BTS while considering minimal cost of infrastructure. The frequency allocation is subject to the constraints defined above. The selected BTS from set I

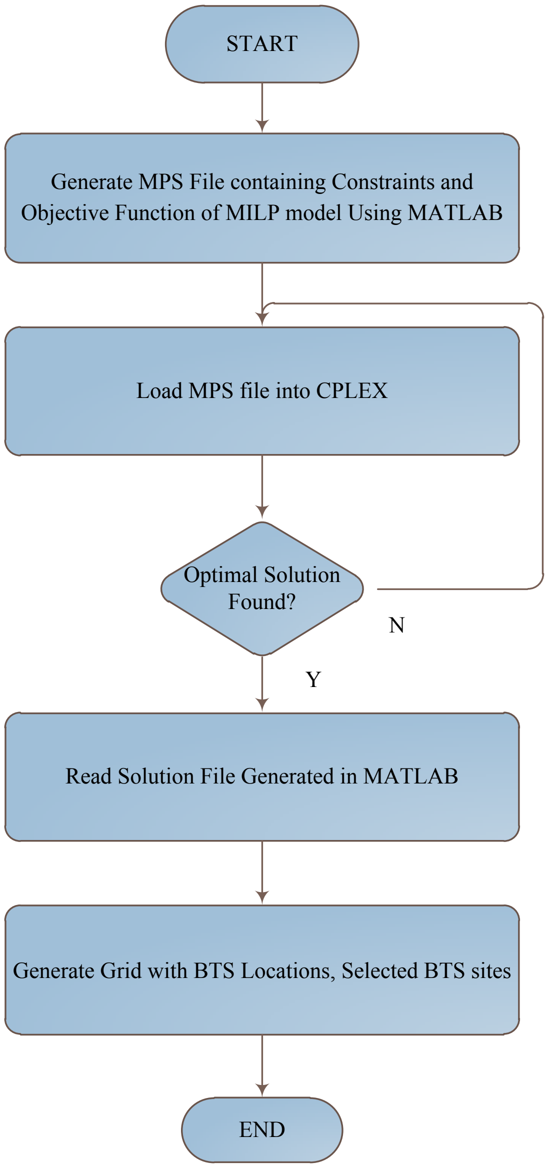


Figure 4.5: Procedure followed for Optimisation Simulation

based on the optimisation solution is shown in figure 4.8. From the 18 BTS, 14 are selected to meet the constraints listed above. The demand per BTS is shown in table 4.4. The demand represents the total demand generated as a result of the demand from

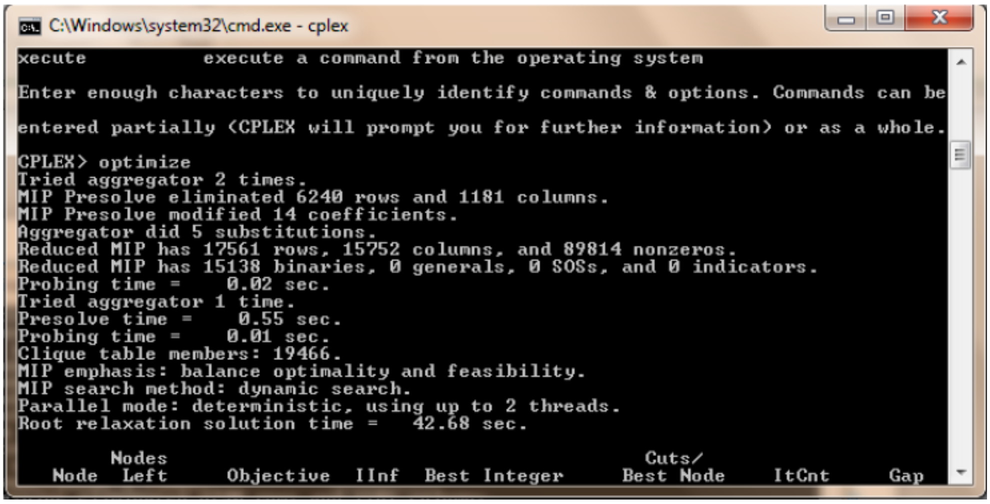


Figure 4.6: CPLEX initiation for Scenario 1

square j and is evaluated as $\sum_{i=1}^{Nbts} x_{ij} d_{jt}$, $\forall t \in T$.

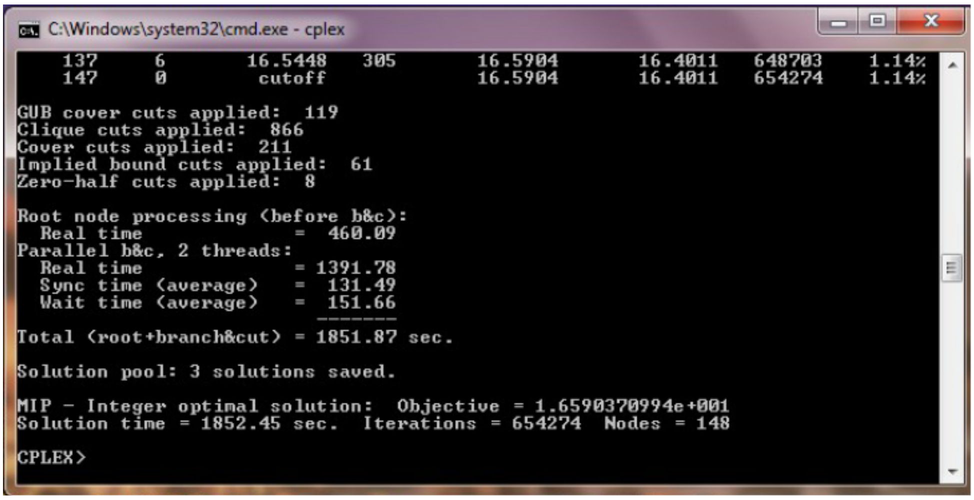


Figure 4.7: CPLEX Output for Scenario 1

The corresponding channel allocation based on the MILP solution for the first case is also shown in table 4.4.

Table 4.3: Performance Results: MILP simulation, Scenario 1

Description	Value
Solution Time	1854.90 sec
Iterations	654274
Nodes	148

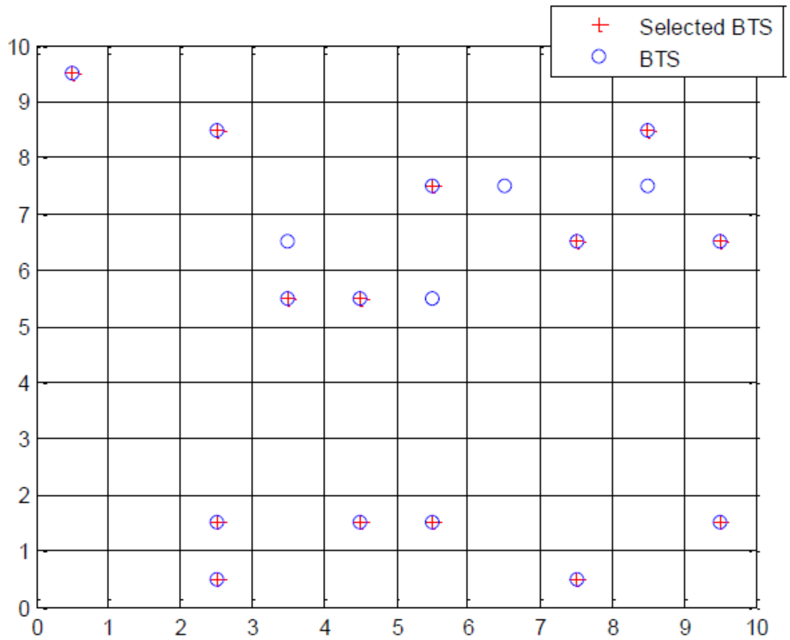


Figure 4.8: Optimal MIP solution considering BTS location and frequency allocation per BTS for Scenario 1

4.7.2 Second Scenario: Increased Cost per Frequency Allocated

Figure 4.9 illustrates the CPLEX initialisation for the second scenario. The corresponding termination reached on finding an optimal solution is shown in figure 4.10. Again, the summary of the performance of the CPLEX solver for the second scenario is given in table 4.5. As in the previous case, the selected BTSs from set I based on the optimisation solution is shown in figure 4.11. From the 18 BTS, 14 are again selected to meet the constraints listed above with a slight variation in the selected BTSs. The added

Table 4.4: Demand per BTS, $\forall i \in I$, Scenario 1

BTS_i	d,t=1	$\sum z_{ik}$,t=1	d,t=2	$\sum z_{ik}$,t=2	d,t=3	$\sum z_{ik}$,t=3	d,t=4	$\sum z_{ik}$,t=4
1	19	19	16	19	8	19	19	19
2	16	19	19	19	18	19	13	13
3	19	9	19	19	17	19	19	19
4	19	19	19	19	16	19	17	19
5	19	18	16	19	17	19	19	19
6	19	19	19	19	18	19	10	14
7	19	18	18	19	19	19	19	19
8	19	19	18	19	19	19	19	19
9	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0
11	19	19	17	19	19	19	19	19
12	19	19	19	19	19	19	17	17
13	19	19	19	19	19	19	19	19
14	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0
16	19	19	19	19	19	19	15	18
17	19	20	19	19	19	19	16	17
18	7	19	19	19	19	19	19	19

cost term is considered in this scenario. As discussed above, the cost term associates an exponential cost value with increase in frequency number. The demand per BTS is shown in table 4.6. It can be seen that the demand per BTS varies from the first scenario. This is due to the variation in the placement that is obtained through the CPLEX solver during BTS selection. The corresponding channel allocation based on the MILP solution for the second case is also shown in table 4.6. The variation in the channel allocation can be seen with reduced channel allocation in some cases. This can be attributed to the increase in costs with rising frequency number.

Table 4.5: Performance Results: MILP simulation, Scenario 2

Description	Value
Solution Time	9410.00sec
Iterations	3775727
Nodes	1774

4.8 Summary of Results

The implementation of the MILP solver for the channel allocation problem that considers a two-level approach to channel allocation was shown in this chapter. From the results obtained, it is shown that a global optimal solution can be achieved in a reasonable amount of time. The impact of the proposed solution links to various aspects of the operational components of a mobile cellular network:

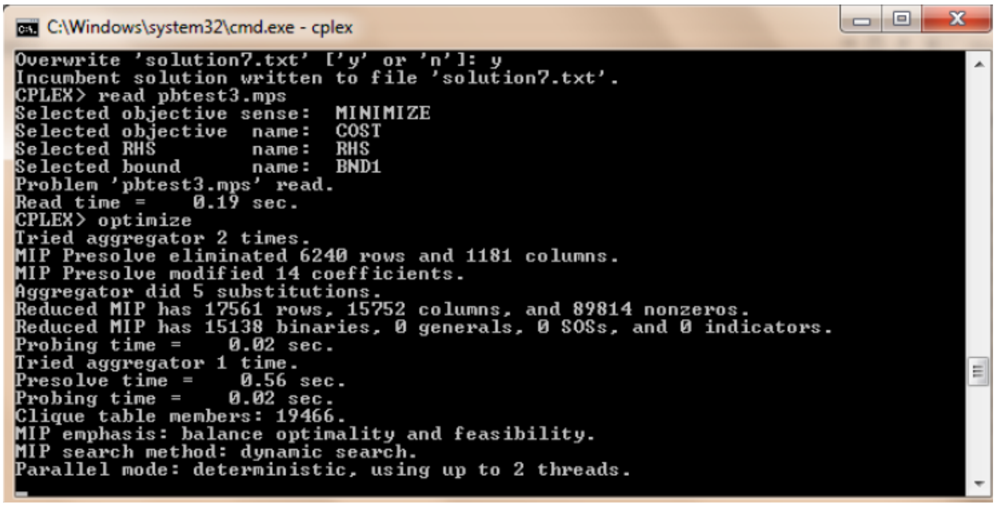


Figure 4.9: CPLEX initiation for Scenario 2

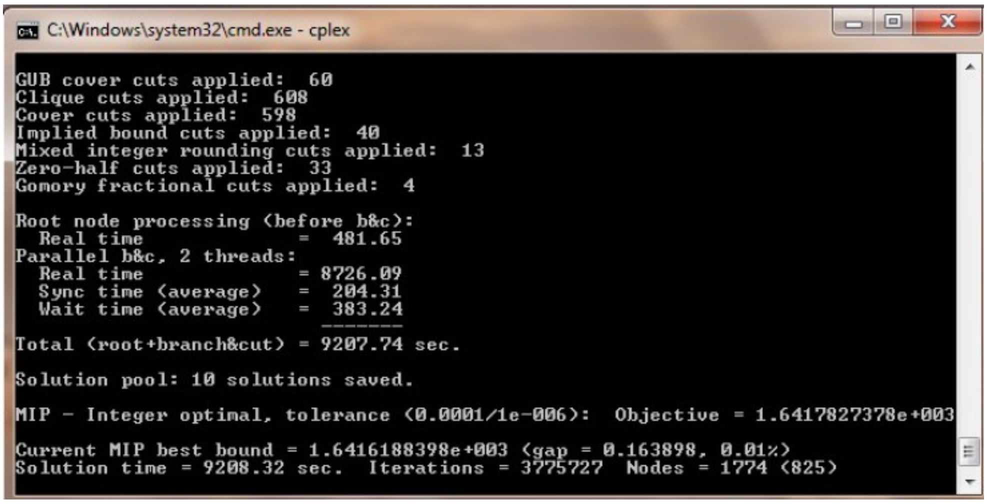


Figure 4.10: CPLEX Output for Scenario 2

1. The variations in the demand for capacity in the network is in many cases not linear, and hence, requires the need to consider a hybrid channel allocation approaches to adapt to the nature of the varying traffic demand experienced in the

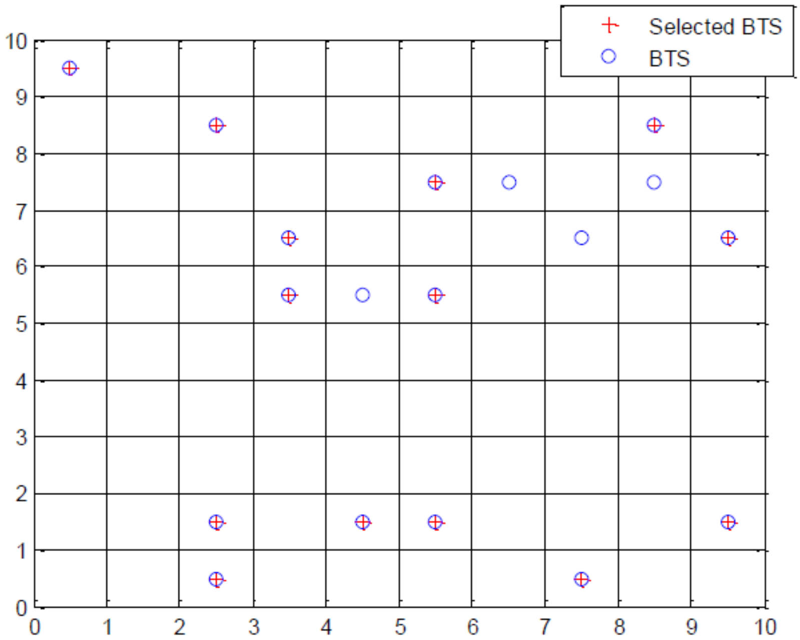


Figure 4.11: Optimal MIP solution considering BTS location and frequency allocation per BTS for Scenario 2

Table 4.6: Demand per BTS, $\forall i \in I$, Scenario 2

BTS_i	d,t=1	$\sum z_{ik}$,t=1	d,t=2	$\sum z_{ik}$,t=2	d,t=3	$\sum z_{ik}$,t=3	d,t=4	$\sum z_{ik}$,t=4
1	19	19	19	19	15	15	19	19
2	19	19	19	19	19	19	11	11
3	19	19	19	19	19	19	19	19
4	19	19	19	19	19	19	19	19
5	19	19	19	19	19	19	19	19
6	19	19	19	19	19	19	19	19
7	19	19	11	11	9	9	11	11
8	0	0	0	0	0	0	0	0
9	18	18	19	19	17	17	16	16
10	17	17	16	16	19	19	19	19
11	0	0	0	0	0	0	0	0
12	19	19	19	19	19	19	19	19
13	17	17	19	19	18	18	19	19
14	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0
16	9	9	19	19	17	17	15	15
17	19	20	19	19	19	19	14	14
18	19	19	19	19	19	19	19	19

network.

2. The Optimisation of available channels in the network using an optimisation

solver such as a MILP solver produces a global optimal solution that takes into account various constraints such as inter-cell interference, intra-cell interference in the channel allocation scheme.

3. Through the proposed approach, the optimisation of BTS placement in terms of site selection for optimal coverage provisioning is achieved.

4. The adapting of network resources to the varying demand of subscriber types in the network is achieved through the adaptive channel allocation scheme.

In the model presented in this chapter, various improvements can be considered. For example, the allocation of a fixed set of channels per period would drastically reduce the complexity of the problem. In addition, the tuning of parameters considered during the search for an optimal solution can improve the performance of the solver. Aspects such as the heuristic that is used during initialisation, the Lagrangian multipliers, duality gaps etc. could lead to better performance of the solver. Some of these aspects could be considered for future studies.

4.9 Conclusion

This chapter presented a novel *two-level* hybrid approach for the channel allocation problem in mobile cellular networks. The chapter first presented a background to the problem and highlighted the proposed channel allocation approach. An overview of mathematical programming approaches and heuristic approaches for solving combinatorial problems was then presented. The Capacitated Facility Location Problem was also highlighted. An overview of the branch-and-bound method was presented together with the concepts on relaxation and duality that are used in the determination of an optimal solution. Based on subscriber classes identified in the previous chapters, the *two-level* hybrid channel allocation scheme that is suited to the demand generated during different time periods in the network is proposed that makes use of a mixed-integer linear programming approach. The use of the MILP approach is used primarily for its simplicity in implementation and the ability of the approach to obtain a global optimal solution. The uniqueness of the proposed approach is the optimisation that takes into account two aspects (and hence the concept of a two-level optimisation model):

1. The first considers a fixed channel threshold allocation ratio which accounts for a maximum threshold of traffic that needs to be considered in a cell. The decision of the ratios are based on the demand expectations as shown.

2. The second aspect of the model considers the optimisation on a period-based dynamic re-allocation of channels which ensures that the network is optimised taking into consideration the variation in demand experienced during various periods of the network.

The channel allocation problem is modelled through the definition of variables and constraints that adhere to general network planning rules. The objective function is defined to take into consideration the minimisation of the number of BTS sites, distance between serving BTS and squares covered by the BTS, and the cost of frequency allocation. Two scenarios were presented to illustrate the impact of varying objective functions. Using IBM's CPLEX MILP solver, it was shown that a global optimal solution can be achieved for the problem modelled in this study.

The overall novelty of the proposed approach highlighted in this chapter is in the use of hybrid channel allocation approach that is *dependant* on time periods. The time period allocation represents the emulation of varying demand according to identified traffic classes from the previous chapters. By integrating the subscriber classification approach shown in the previous chapters and the hybrid channel allocation approach presented in this chapter, a unique adaptive channel allocation scheme that is suited to the mobile subscriber markets considered is achieved.

Chapter 5

Conclusions and Recommendations

5.1 Introduction

This chapter provides concluding remarks of the study. An overview of the objectives of the study is first made. The achievements and contributions of the study is then discussed. The benefits and recommendations for further study is also made. A final conclusion is then made.

5.2 Stated Objectives and Achievements of Study

This study identified two main sub-problems which are stated below:

1. The first sub-problem was to propose a suitable feature extraction approach that is suited for the time series traffic data considered in this study. Based on the features extracted, a classification approach for subscriber traffic class identification needed to be identified.

2. The second sub-problem was to propose a new channel allocation approach that considers the behaviour of the subscriber traffic classes identified in the previous phase. The proposed approach needed to consider the behaviour aspects of the traffic within identified traffic classes.

Based on the above, the following was achieved:

1. An approach for feature extraction in time series data extracted from a mobile cellular network was proposed and demonstrated. The detailed analysis of two different multi-scale approaches (EMD, DWPT), the difference histogram approach, and a modified difference histogram approach was presented. The proposed approach was tested with two different data sets representing two different urban areas in South Africa, one in the South Western part of South Africa and the other in the Central part of South Africa. The data sets were obtained from two different network operators.

2. Based on the extracted features, the classification of extracted features based on a fuzzy C-means clustering algorithm showed that distinct subscriber classes could be identified from the features extracted. This could give an indication of the characteristics of the traffic demands associated to a particular data set which in turn could be used to determine the optimisation strategy and the channel allocation strategy to utilise for the given area.

3. A two-level hybrid channel allocation scheme that makes use of a mixed integer linear programming approach was presented. The formulation of the problem was presented together with variables, constraints, and the formulated objective function considered for the problem. Using IBM's CPLEX MIP solver, it was shown that an optimal solution could be obtained. The proposed model consists of two main parts. The proposed model considers the base station placement problem that allocates BTS based on demand in the network. The proposed model also considers a channel allocation approach that considers different time periods to meet the varying demands of subscriber classes. In this way, the optimal re-optimisation of available resources is ensured.

5.3 Benefits of Study

With the rise in demand for capacity being experienced in most mobile networks around the world, the challenges of network optimisation that takes into account the optimisation of available resources is crucial. Compounded to this problem is the varying traffic demands associated to varying socio-economic factors that contribute to the varying traffic demands in the network.

1. Firstly, a benefit of this work is the ability to determine traffic behaviour from readily available traffic data in the network. For a novice network planner, by conducting the feature extraction and classification approach proposed, the planner is able to determine which traffic class a cell belongs to which could help the planner in making decisions regarding resource allocation and optimisation in the network.

2. Secondly, the two-level hybrid channel allocation scheme provides a simple approach for the optimisation of available resources based on traffic classes and time intervals defined in the optimisation problem. By varying the objective function defined, variations in the optimisation problem that yields optimal solutions is possible with trade-offs being made on different cost functions (for example, the impact of cost of frequency allocations shown in the previous chapter). The net benefit of the proposed approach is in cost saving for a network operator and the ability to ensure that required GOS is provided through the provisioning of minimum number of resources to meet required quality levels in the network. The cost saving is linked to two aspects which play a big role in the mobile networks: Cost of BTSs and the cost of frequencies. These two primary cost elements play a vital role in ensuring the best return for the mobile network operator.

3. A further benefit of the study is the ability to apply the proposed approaches to various other fields that make use of similar time series data for classification purposes. Similar feature extraction and classification approaches could be applied for applications that require feature extraction and classification for similar data sets.

4. The optimisation based approach highlighted in this study could also be utilised for various commodity type problems that involve the optimisation of resource based allocation between varying subscriber demands.

5.4 Contributions of Work

As highlighted above, the primary contributions of this work is twofold: the performance of various feature extraction approaches suited to the time-series traffic data considered was presented. Based on this, the classification of traffic data into distinct subscriber classes was shown. A fuzzy C-means clustering approach was used to show the impact of the features extracted in the classification process. Based on the subscriber classes identified, a hybrid channel allocation scheme that could be adapted to differing time intervals was shown. The proposed approach considered a MILP approach and was solved using the commercial IBM CPLEX MIP solver. It was shown that an optimal solution could be reached for the objective function defined. In contrast to existing approaches for channel allocation, the multi-period based re-optimisation is a novel contribution.

A number of research outputs were generated through the work considered in this study which were presented at various local and international conferences. Furthermore, a number of related work were published at various local and international conferences linked to meta-heuristic approaches for optimisation of resources in 2G/3G networks that made use of genetic algorithms for solving the BTS placement problem.

5.5 Recommendations for Future Study

This work primarily considered the impact of 2G voice traffic. This study could be extended to consider 3G traffic. The implementation of unsupervised training algorithms for the classification of subscriber types could also be considered to implement an automated classification mechanism. Considering the network optimisation part, various aspects of the optimisation model can be tuned to improve the performance of the algorithm. As highlighted previously, the allocation of fixed sets of channels per period could be considered in which z_{ikt} is replaced by a per-time period allocation $\overline{z_{ik}}$. Various aspects of the performance of the optimisation solver could be looked at to improve the performance of the solver such as the Heuristics used during initialisation, the Lagrangian relaxation rules, duality gaps, etc.

5.6 Final Conclusions

The primary objective of a mobile cellular network operator is to minimise the total cost of resources allocated in the network from a Capital Expenditure point of view and from an Operational Expenditure point of view (CAPEX/OPEX) while maximising the total return from users (ARPUs). The identifying of subscriber classes in the network could aid in determining traffic behaviour of subscribers and aid in the network optimisation process. This study provided an feature extraction and classification approach that could be applied to cellular network traffic data extracted from live networks to classify cells into traffic classes. The benefit of conducting the classification/segmentation is in better allocating resources to cells of a particular traffic class.

The complexity of solving the multi-objective optimisation problem for the allocation of channels in the network is simplified through the modelling of the problem as a mixed integer linear programming problem. A novel two-level hybrid channel allocation approach was presented in this study to solve this problem. Using a commercially available MIP solver such as CPLEX, it was shown that an optimal solution could be obtained. The benefit of the proposed approach is the ability of the proposed approach adapting to the varying demands of identified traffic classes using the two-level hybrid channel allocation approach. By using a period based allocation model, a dynamic pool of channels is re-optimised during different periods that correspond to extreme traffic variation periods in the network.

Bibliography

[1] R. Agrawal, C. Faloutsos, and A. Swami, *Efficient similarity search in sequence databases*, In 4th Int. conference on foundations of data organization and algorithms, volume 730, pages 69-84, 1993.

[2] A.N. Akansu and R.A. Haddad, *Multiresolution Signal Decomposition: Transforms, Subbands, and Wavelets*, 2nd Edition, Academic Press, 2001.

[3] A. Baier and K. Bandelow, *Traffic engineering and realistic network capacity in cellular radio networks with inhomogeneous traffic distribution*, IEEE 47th Vehicular Technology Conference (VTC'97), Volume 2, pages 780-784, May 1997.

[4] F. Bao, X. Wang, Z. Tao, Q. Wang, and S. Du, *EMD-based extraction of modulated cavitation noise*, Mechanical Systems and Signal Processing, 24:2124-2136, 2010.

[5] P.B. Biskas, N.P. Ziogos, A. Tellidou, C.E. Zoumas, A.G. Bakirtzis, and V. Petridis, *Comparison of two metahuerisitcs with mathematical programming methods for the solution of OPF*, In IEEE Conference on Generation, Transmission, Distribution, volume 153, pages 16-24, 2006.

[6] A. Borghetti and C. D'Ambrosio,*An MILP approach for short-term hydro scheduling and unit commitment with head-dependant reservoir*, Renewable Energy, 23(3):1115-1124, August 2008.

[7] A. Boukerche, S. Hong, and T. Jacob, *A distributed algorithm for dynamic channel allocation*, Journal on Mobile Networks and Applications, 7:115-126, 2002.

[8] S. Bradley, A. Hax, and T. Magnanti. Applied Mathematical Programming. Addison-Wesley, 1977.

[9] C. Budayan, I. Dikmen, and M.T. Birgonul, *Comparing the performance of traditional cluster analysis, self-organizing maps and fuzzy c-means method for strategic grouping*, Expert Systems with Applications, 36:11772-11781, 2009.

[10] D. Calin, P. Gardell, A. Mackay, T.B. Morawski, Sackett R. Pinson, L., and H. Zhang, *A new approach to capacity growth planning in CDMA networks*, In 12th International Telecommunications Network Strategy and Planning Symposium, pages 1-6, 2006.

[11] G. Cao and M. Singhal, *Efficient distributed channel allocation for mobile cellular networks*, In 7th International Conference on Computer Communications and Networks, pages 50-57, October 1998.

[12] G. Cao and M. Singhal, *An adaptive distributed channel allocation strategy for mobile cellular networks*, Journal on Parallel and Distributed Computing, 60:451-473, 2002.

[13] A. Capone and M. Trubian, *Channel assignment problem in cellular systems: a new model and a Tabu search algorithm*, IEEE Transactions on Vehicular Technology, 48(4):1252-1260, July 1999.

[14] E. Castillo, A.J. Conejo, P. Pedregal, R. Garcia, and N. Alguacil, *Building and Solving Mathematical Programming Models in Engineering and Science (Pure and Applied Mathematics: A Wiley Series of Texts, Monographs and Tracts)*. John Wiley and Sons, 2002.

[15] K. Chakrabarti, E. Keogh, S. Mehrotra, and M. Pazzani, *Locally adaptive dimensionality reduction for indexing large time series databases*, In ACM SIGMOD Conference on Management of Data, pages 151-162, 2002.

[16] K-P. Chan and W. Fu, *A Efficient time series matching by wavelets*, In International Conference on Data Engineering, pages 126-133, 1999.

[17] K.N Chang, J.T. Kim, C.S. Yim, and S. Kim, *An efficient borrowing channel assignment scheme for cellular mobile systems*, IEEE Transactions on Vehicular Technology, 47(2):602-608, May 1998.

[18] C. Chiu, Y. Chen, I. Kuo, and H. Chun Ku, *An intelligent market segmentation system using k-means and particle swarm optimisation*, Expert Systems with Applications, 36:4558-4565, 2009.

[19] A. Danczyk and H.X. Liu, *A mixed-integer program for optimising sensor locations along freeway corridors*, Transportation Research Part B, 45:1208-217, 2011.

[20] S. Das, S. Sen, R. Jayaram, and P. Agrawal, *An efficient distributed channel management algorithm for cellular mobile networks*, In IEEE 6th Conference on Universal Personal Communications, volume 2, pages 646-650, October 1997.

[21] S. K. Das, S.K. Sen, and R. Jayaram,*A dynamic load balancing strategy for channel assignment using selective borrowing in cellular mobile environment*, ACM Journal on Wireless Networks, 3:333-347, 1997.

[22] E. Del Re, R. Fantacci, and G. Giambene, *Handover and dynamic channel allocation techniques in mobile cellular networks*, IEEE Transactions on Vehicular Technology, 44(2):229-237, May 1995.

[23] X. Dong and H. T. Lai, *An efficient priority-based dynamic channel allocation strategy for mobile cellular networks*, In 6th Annual Joint Conference of INFOCOM'97, pages 892-899, April 1997.

[24] M. Duque-Antn, B. Rber, and U. Killat, *Extending Kohonen's self-organizing mapping for adaptive resource management in cellular radio networks*, IEEE Transactions on Vehicular Technology, 46(3):560-568, August 1997.

[25] E. Keogh, K. Chakrabarti, M. Pazzani, and S. Mehrotra, *Dimensionality reduction for fast similarity search in large time series databases*, Knowledge Information Systems, 3(3):263-286, 2001.

[26] S. Ekici, S. Yildirim, and M. Poyraz, *Energy and entropy-based feature extraction for locating fault on transmission lines by using neural networks and wavelet packet decomposition*, Expert Systems with Applications, 34:2937-2944, 2008.

[27] H. Eristi and Y. Demir. *A new algorithm for automatic classification of power quality events based on wavelet transform and SVM*, Expert Systems with Applications, 37:2094-4102, 2010.

[28] H. Eristi, A. Ucar, and Y. Demir, *Wavelet-based feature extraction and selection for classification of power system disturbances using support vector machines*, Electric Power Systems Research, 80:743-752, 2010.

[29] A.M. Gaouda, M.M. Salama, and Chikhani A.Y. Sultan, M.R, *Power quality detection using classification using wavelet-multiresolution signal decomposition*, IEEE Transactions Power Delivery, 14:1469-1476, 1999.

[30] C. Garcia, M. Ernam, W. Egner, and S. Subramanian, *Demand modelling and growth planning for TDMA-based wireless networks*, In IEEE Wireless Communications and Networking Conference (WCNC'99), pages 433-436, 1999.

[31] Gartner,*Gartner says 428 million mobile communication devices sold worldwide in first quarter 2011, a 19 percent increase year-on-year*, `http://www.gartner.com`, May 2011.

[32] A. Goldsmith, *Wireless Communications*, Cambridge University Press, 2005.

[33] F.C. Gomes, P. Pardalos, C.S. Oliveira, and M. G. C. Resende, *Reactive GRASP with path relinking for channel assignment in mobile phone networks*, ACM Journal of Networking, pages 60-67, 2001.

[34] L. Gonzalez-Abril, F. Velasoc, A. Ortega, J., and J. Cuberos, *A new approach to qualitative learning in time series*, Expert Systems with Applications, 36:9924-9927, 2009.

[35] U. Gotzner and A. Gamst,*Capacity of live GSM networks*, In Vehicular Technology Conference, 1998. VTC 98. 48th IEEE, volume 2, pages 1443-1447, May 1998.

[36] F. Gullo, G. Ponti, A. Tagarelli, and S. Greco, *A time series representation model for accurate and fast similarity detection*, Pattern Recognition, 42:2998-3014, 2009.

[37] E. Guney, N. Aras, I.K. Altinel, and C. Ersoy, *Efficient integer programming formulations for optimum sink location and routing in heterogeneous wireless sensor networks*, Computer Networks, 54:1805-1822, 2010.

[38] T. Halonen, J. Romero, and T. Melero, *GSM, GPRS, and EDGE Performance: Evolution Towards 3G/UMTS*, Wiley and Sons, 2003.

[39] L. Hamaza Cherif, S.M. Debbal, and F. Bereksi-Reguig, *Choice of the wavelet analyzing in the phonocardiogram signal analysis using the discrete and packet wavelet transform*, Expert Systems with Applications, 37:913-918, 2010.

[40] J.K Han, B.S. Park, Y.S. Choic, and H.K. Park, *Genetic approach with a new representation for base station placement in mobile communications*, IEEE Vehicular Technology Conference (VTC'01), pages 2703-2701, 2001.

[41] Q. Hao and B. Soong, *A low-cost cellular mobile communication system: A hierarchical optimisation network resource planning approach.*, IEEE Selected Areas in Communications, 15(7):1315-1326, September 1997.

[42] L. He, G-H. Huang, G-M. Zeng, and H-W. Lu, *Wavelet-based multiresolution analysis for data cleaning and its application to water quality management systems*, Expert Systems with Applications, 35:1301-1310, 2008.

[43] P.H. Hiew and M. Zukerman, *Efficiency comparison of channel allocation schemes for digital mobile communication networks*, IEEE Transactions on Vehicular Technology, 49(3):724-733, May 2000.

[44] G.S. Hu, F.F. Zhu, and Z. Ren, *Quality disturbance identification using wavelet packet energy entropy and weighted support vector machines*, Expert Systems with Applications, 35:9776-9783, 2008.

[45] IBM, *IBM ILOG CPLEX v12.1: User's manual for CPLEX*, `http://www.ibm.com`, 2009.

[46] IBM, *IBM ILOG CPLEX optimisation studio*, `http:/www-01.ibm.com/software/integration/optimization/cplex-optimization-studio/`, 2011.

[47] Z. Iscan, Z. Dokur, and T. Demiralp, *Classification of electroencephalogram signals with combined time and frequency features*, Expert Systems with Applications, 38:10499-10505, 2011.

[48] ITU-D, *ICT in Africa: Forging a competitive edge*, `http://www.itu.int/ITU-D/connect/africa/2007/media/kit/africa_ict.html`, April 2004.

[49] ITU-D, *Information society statistical profiles 2009: Africa*, `http://www.itu.int`, October 2009.

[50] ITU-D, *The world in 2009: ICT facts and figures*, `http://www.itu.int`, October 2009.

[51] ITU-D, *The world in 2010: The rise of 3G*, `http://www.itu.int`, October 2010.

[52] Connect Africa Summit ITU Report, *Telecommunication/ICT markets and trends in Africa - 2007*, `http://www.itu.int`, October 2007.

[53] Z. Jagnjic, N. Bougunovic, I. Pizeta, and F. Jovic, *Time series classification based on qualitative space fragmentation*, Advanced Engineering Informatics, 23:116-129, 2009.

[54] J. Jiang, T.H. Lai, and N. Soundarajan,*On distributed dynamic channel allocation in mobile cellular networks*, IEEE Transactions on Parallel and Distributed Systems, 13(10):1024-1037, October 2002.

[55] R.W. Juma, K. Djouani, and A. Kurien, *A mathematical approach for capacity enhancement in 3G mobile networks*, Southern Africa Telecommunication Networks and Applications Conference (SATNAC'11), September 2011.

[56] C. Junsheng, Y. Dejie, and Y. Yu, *A fault diagnosis approach for roller bearings based on EMD method and AR model*, Mechanical Systems and Signal Processing, 20:350-362, 2006.

[57] I. Katzela and M. Naghsineh, *Channel assignment schemes for cellular mobile telecommunication systems: A comprehensive survey*, IEEE Journal on Personal Communications, pages 10-31, June 1996.

[58] E. Keogh, S. Chu, D. Hart, and M. Pazzani, *An online algorithm for segmenting time series*, International conference on data mining (ICDM), pages 289-296, 2001.

[59] E.J. Keogh and M.J. Pazzani, *Relevance feedback retrieval of time series data*, 22nd International ACM-SIGIR Conference on Research and Development in Information Retrieval, pages 183-190, August 1999.

[60] H. Khedher, F. Valois, and S. Tabbane, *Real mechanisms for mobile network modelling and engineering*, Global Telecommunications Conference (GLOBECOM' 04), volume 4, pages 2134-2139, November 2004.

[61] K. Kianmehr and R. Alhajj, *Calling communities analysis and identification using machine learning techniques*, Expert Systems with Applications, 36:6218-6226, 2009.

[62] S.H. Kim, K.N. Chang, and S. Kim, *A channel allocation for cellular mobile radio systems using simulated annealing*, Springer Journal on Telecommunication Systems, 14:95-106, August 2000.

[63] F. Korn, H.V. Jagadish, and C. Faloutsos, *Efficiently supporting ad-hoc queries in large datasets of time sequences*, ACM SIGMOD Conference on Management of Data, pages 289-300, 1997.

[64] K. Kritikos and D. Plexousakis, *Mixed-integer programming for QoS-based web service match making*, IEEE Transactions on Services Computing, 2(2):122-139, April 2009.

[65] A. Kurien, K. Djouani, B.J. Van Wyk, Y. Hamam, and A. Mellouk, *Using empirical mode decomposition for subscriber behaviour analysis in cellular networks in South Africa*, IEEE 7th International Multi-Conference on Systems, Signals and Devices (SSD'10), pages 1-5, June 2010.

[66] A.M. Kurien, G. Noel, A. Mellouk, B.J. Van wyk, and K. Djouani,*Efficient classification based on multi-scale traffic data extraction patterns of cellular networks*, In 6th International Wireless Communications and Mobile Computing Conference IWCMC'10, pages 361-365, June 2010.

[67] A.M. Kurien, B.J. Van Wyk, L.W. Snyman, and D. Chatelain, *Intelligent planning of mobile networks for Southern Africa*, EUROSIM Special Session on Modelling and Simulation of Distributed Systems and Networks, 2004.

[68] I. Laki, L. Farkas, and L. Nagy, *Cell planning in mobile communication systems using sga optimisation*, IEEE Conference on Trends in Communications (EURCON'01), pages 124-127, 2001.

[69] C.Y. Lee and H.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.

[70] J. Lempiainen and M. Manninen, *Radio Interface Systems Planning for GSM/GPRS/UMTS*, Kluwer Academic Publishers, 2002.

[71] J. Li, Z. Yunlong, and S. Hai, *An improved branch and bound algorithm for location-routing problems*, IEEE International Forum on Computer Science,Technology and Applications, pages 58-63, 2009.

[72] J. Lin, E. Keogh, S. Lonardi, and B. Chiu, *A symbolic representation of time series, with implications for streaming algorithms*, 8th ACM SIGMOD Workshop on Research Issues in Data Mining and Knowledge Discovery, pages 2-11,June 2003.

[73] L. Lin and J. Hongbing, *Signal feature extraction based on an improved EMD method*, Measurement, 42:796-803, 2009.

[74] P. Luathep, A. Sumalee, W.H.K. Lam, and Lo H.K. Li, Z, *Global optimization method for mixed transportation network design problem: A mixed-integer linear programming approach*, Transportation Research Part B, 45:808-827, 2011.

[75] M. Mahdian and M. Pal, *Universal facility location*, 11th Annual European Symposium on Algorithms, pages 409-421, September 2003.

[76] S. Mallat, *A Wavelet Tour of Signal Processing: The Sparse Way*, 3rd Ed., Academic Press, 2009.

[77] Mathworks, *Matlab 2011a*, `http://www.mathworks.com`, 2011.

[78] F.F. Mazzini and G.R. Mateus, *A mixed-integer programming model for the cellular telecommunication network design*, ACM Journal of Networking, pages 68-76, 2001.

[79] C. Mazzoni, L. Castaldi, and F. Addeo, *Consumer behaviour in the Italian mobile communication market*, Telecommunications Policy, 31:632-647, 2007.

[80] A.R. Mishra, *Advanced Cellular Network Planning and Optimisation: 25/2.5G/3G...Evolution to 4G*, Wiley and Sons, 2007.

[81] R.E.N. Moraes, C.C. Ribeiro, and C. Duhamel, *Optimal solutions for fault-tolerant topology control in wireless ad-hoc networks*, Transportation Research Part B, 8(12):5970-5981, December 2009.

[82] H. Morais, P. Kadar, P. Faria, Z.A. Vale, and H.M. Khodr, *Optimal scheduling of renewable micro-grid in an isolated load area using mixed-integer linear programming*, Renewable Energy, 35:151-156, 2010.

[83] J. Munyaneza, B.J. Van Wyk, and A. Kurien, *Optimisation of antenna placement in 3G networks using genetic algorithms*,3rd International Conference on Broadband Communications, Information Technology and Biomedical Applications (BroadCom'08), pages 463-467, November 2008.

[84] M. Oughdi, A. Caminada, S. Lamrous, and B. Morin, *Load regulation on mobile network with planned pricing model based on user behaviour*, Joint International Conference on Autonomic and Autonomous Systems and Networking and Services (ICAS/ICNS), pages 53-59, October 2005.

[85] B.S. Park, J. Yook, and H.K. Park, *The determination of base station placement and transmit power in an inhomogenous traffic distribution for radio network planning*, IEEE Vehicular Technology Conference (VTC'02), pages 2051-2055, 2002.

[86] P. Peilin and D. Guangbin, *Power quality detection and discrimination in distributed power systems based on wavelet transform*, IEEE 27th Chinese Control Conference, pages 635-638, 2008.

[87] B.R. Philemon, A. Kurien, and Y. Hamam, *The optimization of base station site placement for unevenly distributed traffic using a genetic algorithm*, IASTED International Conference on Modelling and Simulation (AfricaMS 2008), September 2008.

[88] B.R. Philemon, A. Kurien, and Y. Hamam,*Base station placement for uneven traffic in cellular networks using genetic algorithm*, 3rd IASTED International Conference on Modelling and Simulation (AfricaMS 2010), September 2010.

[89] A. Phinyomark, C. Limsakul, and P. Phukpattaranont, *Optimal wavelet functions in wavelet denoising for multifunction myoelectric control*, ECTI Transactions on Electrical Engineering, Electronics, and Communications, 8(1):43-52, 2010.

[90] G.R. Raidl and J. Puchinger, *Combining (integer) linear programming techniques and meta-heuristics for combinatorial optimisation*, Studies in Computational Intelligence (SCI), 114:31-62, 2008.

[91] T. Rapaport, *Wireless Communications: Principles and Practise*, Pearson Education, 2009.

[92] D. Reeve, Y. Li, M. Lark, and D. Simmonds, *An investigation of the multi-scale temporal variability of beach profiles at duck using wavelet packet transforms*, Coastal Engineering, 54:410-415, 2007.

[93] G. Rilling, P. Flandarin, and P. Goncalves, *On empirical mode decompostion and its algorithms*, IEEE EURASIP Workshop on Non-linear and Image Processing (NSIP), volume 3, pages 8-11, 2003.

[94] H.G. Sandalidis, P.P. Stavroulakis, and J. Rodriguez-Tellez, *An efficient evolutionary algorithm for channel resource management in cellular mobile systems*, IEEE Transactions on Evolutionary Computation, 2(4):125-137, November 1998.

[95] H.G. Sandalidis, P.P. Stavroulakis, and J. Rodriguez-Tellez, *Borrowing channel assignment strategies based on heuristic techniques for cellular systems*, IEEE Transactions on Neural Networks, 10(1):176-181, January 1999.

[96] E. Sejdic, I. Djurovic, and J. Jiang, *Time-frequency feature representation using energy concentration: An overview of recent advances*, Digital Signal Processing, 19:153-183, 2009.

[97] P. Shan and M. Li, *Nonlinear time-varying spectral analysis: HHT and MOD-WPT*, Hindawi Journal on Mathematical Problems in Engineering, pages 1-14, 2010.

[98] S.Y. Sohn and Y. Kim, *Searching customer patterns of mobile service using clustering and quantitative association rule*, Expert Systems with Applications, 34:1070-1077, 2009.

[99] M. St-Hilaire and S. Liu, *Comparison of different meta-heuristics to solve global planning problem in UMTS networks*, Computer Networks, 55:2705-2716, 2011.

[100] R. Subrata and A.Y. Zomaya, *Artificial life techniques for reporting cell planning in mobile computing*, In International parallel and Distributed Processing Symposium (IPDPS'02), pages 203-210, 2002.

[101] R. Subrata and A.Y. Zomaya, *A comparison of three artificial life techniques for reporting cell planning in mobile computing*, IEEE Transactions on Parallel and Distributed Systems, 14(2):142-153, February 2003.

[102] M.J. Todd, *The many facets of linear programming. Mathematical Programming Series*, 91:417-436, 2002.

[103] D. Tsai and C. Lin, *Fuzzy C-means based clustering for linearly and nonlinearly separable data*, Pattern Recognition, 44:1750-1760, 2011.

[104] K. Tutschku, *Demand-based radio network planning of cellular mobile communication systems*, Technical Report Vol. 2, No. 177, Institute of Computer Science, University of Wrzburg, July 1997.

[105] K. Tutschku, *Demand-based radio network planning of cellular mobile communication systems*, IEEE Conference on Computer Communication (INFOCOM), volume 1, pages 1054-1061, April 1998.

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

[107] K. Tutschku and P. Tran-Gia, *Spatial traffic estimation and characterisation for mobile communication network design*, IEEE Selected Areas in Communications, 16(5):804-811, June 1998.

[108] M. Uyar, S. Yildirim, and M.T. Gencoglu, *An effective wavelet-based feature extraction method for classification of power quality disturbance signals*, Electric Power Systems Research, 78:1747-1755, 2008.

[109] B.J. Van Wyk, M.A. Van Wyk, and G. Qi, *A new tool for time series analysis applied to bearing fault diagnosis*, Pattern Recognition Letters, 30:595-599, 2009.

[110] F. Vatansever and A. Ozdemir, *Power parameters calculation based on wavelet packet transform*, Electrical Power and Energy Systems, 31:596-603, 2009.

[111] G. Vidyarthi, A. Ngom, and I. Stojmenovic, *A hybrid channel assignment approach using an efficient evolutionary strategy in wireless mobile networks*, IEEE Transactions on Vehicular Technology, 54(5):1887-1895, September 2005.

[112] J. Vygen, *Approximation algorithms for facility location problems: Lecture notes*, Technical report, Research Institute for Discrete Mathematics,University of Bonn, 2005.

[113] G. M. Weiss. Data mining in telecommunications. In Maimon O. and Rokach L., editors, Data Mining and Knowledge Discovery Handbook: A Complete Guide for Practitioners and Researchers, pages 1189-1201. Kluwer Academic Publishers, 2005.

[114] F. Wesselmann, A. Koberstein, and U.H. Suhl, *Pivot-and-reduce cuts: An approach for improving gomory mixed-integer cuts*, European Journal on Operational Research, 214:15-26, 2011.

[115] R.M. Whitaker, L. Raisanen, and S. Hurley, *The infrastructure efficiency of cellular networks*, Computer Networks, 48:941-959, 2005.

[116] I.H. Witten and E. Frank, *Data Mining: Practical Machine Learning Tools and Techniques*, Morgan Kaufmann, San Francisco, 2005.

[117] J.D. Wu and J.M. Kuo, *An automotive generator fault diagnosis system using discrete wavelet transform and artificial neural network*, Expert Systems with Applications, 36:9776-9783, 2009.

[118] X. Wu, A. Jaekel, A. Bari, and A. Ngom, *Optimized hybrid resource allocation in wireless cellular networks with and without channel reassignment*, Journal of Computer Systems, Networks and Communication, pages 1-11, July 2010.

[119] Y. Youn, H. Jeon, H. Juung, and H. Lee, *Discrete wavelet packet transform based energy detector for cognitive radios*, IEEE 65th Vehicular Technology Conference (VTC'07), pages 2641-2645, 2007.

[120] Y. Zhang and S. K. Das, *An efficient load-balancing algorithm based on a two threshold cell selection scheme in mobile cellular networks*, Journal of Computer Communications, 23:452-461, 2000.

[121] C. Zhao and L. Gan, *Dynamic channel assignment for large-scale cellular networks using noisy chaotic neural network*, IEEE Transactions on Neural Networks, 22(2):222-232, February 2011.

[122] K. L. Hoffman and T.K. Ralphs, *Integer and Combinatorial Optimization*, Encyclopedia of Operations Research and Management Science, 2011.

Appendix A

Related Background on Mobile Networks

A.1 Introduction

This Appendix provides an overview of basic concepts of GSM networks. The main focus is on channel allocation strategies proposed to manage the radio resource allocation in mobile cellular networks.

A.2 Basic GSM Network Structure

The Global System for Mobile (GSM), originally coined as the Group Speciale Mobile in 1982, was originally developed as a 2nd generation digital technology for the European market, but covers over 71% of the world market today according to the GSM Association (GSMA). One of the objectives of the system was to target reduced cost of coverage for the technology. A simplified architecture of a typical GSM network is presented in figureA.1. The system highlights the base station subsystem (glsbss) and the network subsystem (NSS). The basis for a cell is defined by the radius of coverage provided by a BTS. To ensure optimal coverage of a given area, the BTS are spread over a service area in such a way that coverage and capacity requirements are fulfilled through the ideally placed BTS. A mobile station (MS) usually communicates with the closest BTS to ensure that required Signal-to-Noise Interference Ratio (SINR) requirements are fulfilled between the BTS and the MS.Base station sites are aggregated through a Base Station Controller (BSC) into Mobile Switching Centres (MSC) which are interconnected to back hauling mechanisms.

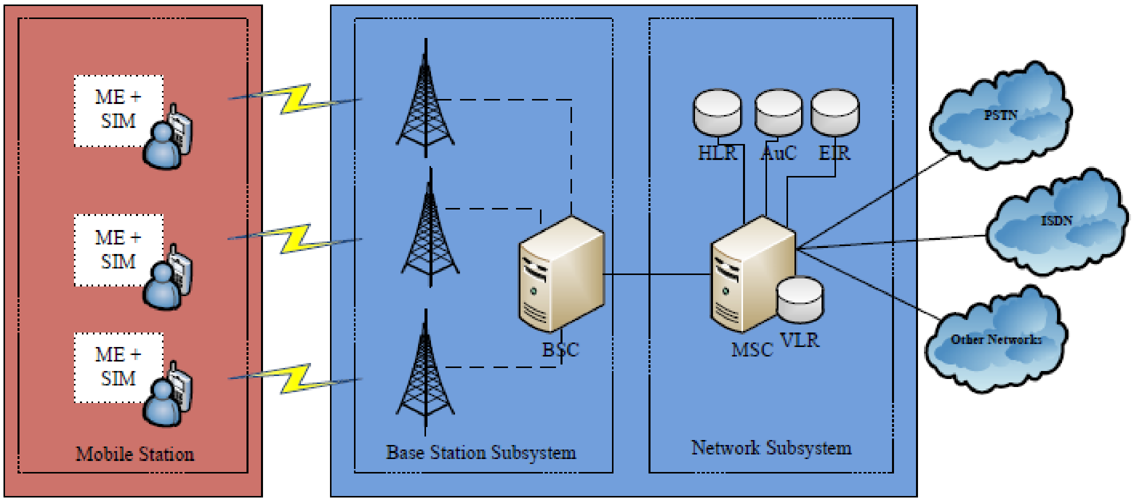


Figure A.1: Basic structure of a typical GSM network

A.2.1 Overview of GSM Physical and Logical Channels

The GSM standard is based on a multi-carrier, time-division multiple access (TDMA) and frequency division duplex (FDD) [38]. A TDMA frame in GSM is subdivided into eight time slots. Each of these slots can be assigned to a full-rate (FR) traffic channel, two half-rate (HR) traffic channels or one of the control channels [38]. Channels in GSM can be split into two categories: $physical$ and $logical channels$. A physical channel corresponds to a time slot on one carrier while a logical channel refers to the specific type of information carried by the physical channel [38]. Logical channels are divided into two groups namely $control$ channels and $traffic$ channels. Traffic channels are used to carry user data which can be either speech or data [38, 80]. In a GSM system, a logical traffic channel is used for speech or circuit-switched data and is called a TCH [38]. A Control Channel is referred to as a CCH. The control channels are used to carry signalling and control information. The channel specification is an important aspect in network dimensioning and in ensuring that sufficient capacity is available in a network.

A.2.2 Channel Allocation in Mobile Cellular Networks

In 1946, public mobile telephone systems were introduced in the USA across 25 cities that made use of central transmitters that covered entire metropolitan areas [32]. The inefficiencies and limitations with regard to technologies limited the number of users that could be supported by these systems. The cellular concept grew from the objective of overcoming these limitations. The concept of fading is utilised as a mechanism to re-use frequencies at stipulated distances that ensures that signal interference does not exist between two users using the same frequency [91]. This strategy has lead to the efficient use of available spectrum that accommodates a larger number of users [32]. In a typical cellular system, a part of the radio frequency spectrum is subdivided into a number of channels. Each BTS is assigned a subset of the channels to serve a MS in the mobile network. Considering a network consisting of S allocated duplex channels, assuming that each cell is allocated k channels and assuming that there are N cells in the network, then the total capacity in the network can be expressed as [91]:

$$S = kN \tag{A.1}$$

Assuming that the above allocation represents a cluster, then the total capacity of a network consisting of M clusters can be expressed as [91]:

$$C = MkN = MS \tag{A.2}$$

Hand over mechanisms are implemented in the network to cater for mobility of MS in the network. When an MS leaves the coverage area of one BTS and enters another, the MS needs to be catered for as it passes from one BTS coverage region to the next.

A.2.3 Channel Allocation Strategies

To ensure that the network is able to provide for the capacity requirement of mobile subscribers in the network, sufficient capacity needs to be provided per cell in the network. This forms part of the channel allocation strategy employed in the network to ensure requested demand is catered for when a call request arrives in the network. The efficiency of the channel allocation scheme ensures the ability of the network to serve the received call and determine if the network can cater to the request or must drop the call due to insufficient capacity in the network. Various channel allocation schemes have been proposed over the years. An overview of the various channel allocation schemes is given in the following sections.

A.2.4 Fixed Channel Allocation Strategies

A typical strategy to determine the total capacity within a network is to determine the total theoretical traffic capacity across all cells within the network [3]. Based on [3] and [35], the theoretical capacity of a network Z consisting of cells $z_i, i = 1, \ldots, N$ can be defined as

$$C_T = \sum_{i=1}^{N} c_i \tag{A.3}$$

The allocated capacity within the network needs to fulfil the condition $y_i < c_i$ where y_i represents the traffic load generated in z_i. It is assumed that a fixed number of traffic channels, m_i, is allocated to each cell z_i [35]. However, to cope with the non-homogeneous nature of traffic generated in networks, a realistic capacity allocation approach needs to be considered. [3] and [35] propose differing approaches to the capacity allocation problem. According to [35], the load factor η_i of cell z_i is given by

$$\eta_i = \frac{y_i}{C_i}, \tag{A.4}$$

where y_i is the traffic load experienced in cell z_i and C_i represents the installed capacity. To cater for the realistic capacity required in cell z_i, the authors in [35] utilise a measured traffic load that experiences linear growth defined by

$$y_i^{'} = (1 + \delta)y_i, \delta > 0 \tag{A.5}$$

The total traffic based on the above growth, $Y^{'}$, is given by [35]

$$Y^{'} = (1 + \delta)Y, \tag{A.6}$$

where Y represents the total traffic in the network. To obtain the most realistic capacity allocation, the largest value of δ is preferred which would imply the largest value for

Y'. This implies that the minimum value for $\frac{1}{\eta_i}$ is assumed. The realistic capacity in the network could then be represented as [35]

$$C_R = Y \min_i \frac{1}{\eta_i}, i = 1, \ldots, N \tag{A.7}$$

The primary components that determine the cell capacity depends on equipment installed, the number of frequency channels available to the operator and the minimum grade of service. In any cellular network, the network optimisation strategy employed from the initial network provisioning considers an optimisation strategy that aims to improve the allocation of available channels to cater for the non-homogeneity of traffic generated in each cell. The methodology employed for the assigning of suitable channels for a received call received in the cell is referred to as the *channel assignment problem*. The channel assignment mechanism is critical in a cellular system in determining the capacity of the network and for ensuring efficient channel utilisation. The channel allocation problem has been widely studied with various approaches having been proposed. A comprehensive survey of channel assignment techniques is given in [57]. The basic strategy of channel allocation is to assign a fixed set of channels to each cell with frequency re-use taking place at a minimum re-use distance [17, 21, 57, 95]. The acceptable distance for channels to be reused is referred to as the co-channel reuse distance. It can be shown that the minimum re-use distance is a function of the radius R_i of a cell z_i. Due to the potential of allocated channels being insufficient to carry traffic within specific cells, channel borrowing schemes have been proposed [57]. Channels can be borrowed from lender cells provided that the channels borrowed do not contribute to interference between cells. As channels are borrowed, a *channel blocking* scheme is employed to prevent the borrowed channel from being used by other cells [57].

A.2.5 Dynamic Channel Allocation Strategies

Due to the non-homogeneity of traffic over time and the inefficiencies introduced when using fixed channel allocation schemes, various dynamic channel allocation schemes have been proposed. In Dynamic Channel Allocation (DCA) schemes, the available channels are grouped into a common pool of channels. Based on a request for channels, the required channels are allocated through a channel allocation approach [17, 21, 57, 95]. Once a call has been completed, the allocated channel is freed to the pool of available channels [57]. The allocation scheme needs to ensure that allocated channels adhere to non-interference for channels allocated to cells. Dynamic channel allocation can be per call or based on an adaptive allocation basis based on the state of the network [57]. An overview of the DCA approach as described in [22] is given below.

Assume that there are M available channels in a network Z consisting of cells z_i, $i = 1, \ldots, N$. As a first allocation, each cell, z_i is assumed to be allocated an initial set of channels according to the fixed channel allocation strategy defined as

$$C = \frac{M}{K}, \tag{A.8}$$

where $K = \frac{D^2}{3R^2}$. D represents the minimum reuse distance between cells and R represents the regular side of a hexagon representing the dimension of a cell. An allocation cost can be defined to ensure that channels c_i allocated to cell z_i are utilised fully. From [22], an allocation cost may be defined as

$$C_{j,k} = u_j(k) + 2(1 - q_j(k)), \forall j \in I(z_i), \tag{A.9}$$

where $I(z_i)$ represents the cells that are less than D from z_i, $u_j(k)$ and $q_j(k)$ are defined as [22]

$$u_j(k) = \begin{cases} 1 & \text{if k} \in \Lambda(j) \\ 0 & \text{otherwise} \end{cases} \tag{A.10}$$

$$q_j(k) = \begin{cases} 0 & \text{if k} \in F_D(j) \\ 1 & \text{otherwise,} \end{cases} \tag{A.11}$$

where $\Lambda(j)$ represents available channels and $F_D(j)$ represents the fixed channels allocated to a cell. The overall cost function can be defined as [22]

$$C_x(k) = q_{z_i}(k) + \sum_{j \in I(z_i)} C_{z_i}(j,k), \forall k \in \Lambda z_i \tag{A.12}$$

For calls that arrive at a particular cell, z_i, and assuming that the available channels in a cell $\Lambda(z_i)$ is not empty, the criteria for the request for allocation of channel $k^{'}$ can be defined as [22]

$$C_{z_i}(k^{'}) = \min_{k \in \Lambda(z_i)} C_{z_i}(k) \tag{A.13}$$

When a channel needs to be released back into the pool of available channels due to termination of a call, it is shown in [22] that better performance is achieved if a de-allocation criteria is used for channel release. Assuming that $A(z_i)$ are the channels used in cell z_i at the point of release, the de-allocation cost function for channel $l \in A(zi)$ is given by [22]

$$R_{z_i}(j,l) = b_{z_i}(j,l)2q_k(l), \forall j \in I(z_i) \tag{A.14}$$

where b_{z_i} is defined by [22]

$$b_{z_i} = \begin{cases} 0 & \text{if channel } l \text{ is locked in } j \\ 1 & \text{otherwise,} \end{cases} \tag{A.15}$$

The overall cost function for channels that require de-allocation can be defined as [22]

$$R_{z_i} = 1 = q_{z_i}(l) + \sum_{j \in I(z_i)} R_{z_i}(j,l), \forall l \in A(z_i) \tag{A.16}$$

The first part of the expression is included to ensure that the

xed channels that are allocated within cell z_i are not de-allocated during the release process. The criteria for the de-allocated channel, $l^{'} \in A(z_i)$ can be defined based on [22]

$$R_{z_i}(l^{'}) = \min_{l \in A(z_i)} R_{z_i}(l) \tag{A.17}$$

It should however be noted that a trade of exists between fixed allocation and dynamic allocation strategies. As the traffic load in the network increases, the performance of dynamic allocation strategies deteriorates with the increased complexity introduced by dynamic allocation strategies.

A.2.6 Hybrid Channel Allocation Strategies

Hybrid channel allocation (HCA) approaches seek to combine features of fixed and dynamic allocation techniques. In this approach, the available channels are separated into two sets: a set of the total channels are allocated as a fixed set and the remaining are dynamically allocated [17, 57, 118]. The allocation of channels from the dynamic set are based on typical DCA allocation algorithms [57]. A variation of the above is the flexible channel allocation strategy in which fixed channels are allocated to each cell and a flexible set are assigned to cells that experience shortage of cells [21, 57].

As discussed in [94] and in [111], representative ratios (35:35, 49:21, and 21:49) are used to represent fixed and dynamic channels allocated. The ratio of the separation of channels to fixed and dynamic sets are preset by the network provider [94, 118]. The performance evaluation and the impact of each allocation is shown. As discussed in [94], the choice of a suitable HCA scheme is dependant on the designer's choice for performance when considering blocking probability or time performance.

A.3 Conclusion

This Appendix provided a basic overview of GSM networks with an emphasis on channel allocation strategies employed. The basis for the channel allocation strategies proposed in literature are considered in the *two-level* hybrid channel allocation model proposed in this study.

Appendix B

Related Work on Capacity Optimisation in Mobile Cellular Networks

B.1 Introduction

This appendix provides an overview of related work considered for capacity optimisation in mobile cellular networks. The focus of the work considered the use of bio-inspired techniques for the optimisation of resources in 2G and 3G networks.

B.2 Radio Network Planning Process

The fundamental task of radio planning of a cellular network is to obtain a network design that is optimal. This focuses on providing the best coverage and capacity for a service area under consideration. Traditional steps taken into consideration in a radio planning tool would include the following steps.

1. A Network Definition phase that determines the ideal number of transmitter locations in the area under consideration.

2. Radio Frequency Propagation Analysis that takes into account the signal propagation related to terrain which provides an indication of coverage patterns.

3. A Frequency Allocation phase that begins the process of allocating appropriate frequencies to the network adhering to co-channel and adjacent channel allocation rules.

Once the above steps have been undertaken, the performance of the network is analysed, and network optimisation is taken into consideration to improve the network design [104, 105, 106]. The planning of the network may focus on *coverage* which takes into consideration the number of sites that are required to cover the geographical area or on *capacity* which takes into account the amount of traffic that needs to be supported within the considered geographical area based on the number of users (subscribers) in the given area. Network dimensioning for mobile services thus takes into consideration different network configurations that satisfy requirements for coverage of the area under study, capacity of sites to support the required traffic volumes, and addressing the issue of grade of service requirements for services to ensure that a network operator remains competitive within the market. With the growth of cellular mobile networks and the introduction of new technologies coupled with newer services, greater demands and challenges are being placed on the traditional network planning approaches and on radio planning tools [105]. Traditional radio planning tools have primarily focused on planning networks from an analytical approach that focuses on radio propagation and interference analysis [106]. Priority is given to providing optimum coverage in areas being planned for while capacity related issues are addressed in later parts of the planning process.

The traditional methods of radio planning are gradually in the process of evolution. Cost is a key element in determining the economic feasibility of any communication system [41]. A move towards the use of statistical information from the environment is considered as a substantial contributing factor towards the planning of networks that are more optimal and cost-effective which is critical in the context of developing countries such as in Africa. With the varying demographics and socio-economic status of most sectors, effective methods need to be integrated into the planning process to perform effective information extraction which could be vital for the planning process as well as to perform the task of adaptive network design.

B.3 Capacity Optimisation in Mobile Cellular Networks using Combinatory Optimisation approaches

As discussed in [67], various studies have been implemented in which adaptive network design methodologies are utilised in the design of modern day cellular networks. These approaches focus on various optimisation goals within the network and consider the use of algorithmic approaches that focus on meeting optimisation targets within the network. A primary goal of any planning strategy is to minimise overall cost [41] of a network without compromising the capacity and quality of the network. The starting point of the planning process would be first to determine the required capacity of cells within a specified area being planned for. The estimation of the capacity is based on the number of subscribers within the area to be planned for and is influenced by the type of services required by the subscribers. Using basic radio propagation path loss models, the optimum radius of a cell can be determined. From this calculation, the total number of required cells for the service area may then be evaluated. As highlighted earlier, this approach represents the analytic approach of cellular network development.

One of the aspects of the above process is the determination of optimal base station site placement that meets the coverage and capacity requirements identified above. The optimisation of base station placement may be done by iteratively acting upon sites selected and inducing the sites to change to better sites adapted to the environment [24, 68, 85]. The use of genetic algorithms for the solving of the base station placement problem is shown in [87], [88], and [83]. The base station placement problem may be formulated as follows. Consider a service area that needs to be covered. The first objective is to determine the optimum number of base station sites required to meet the coverage requirements.

Consider that N_{bts} is the minimum number of base station sites required to provide coverage to the given service area. A given service area may be split into two sets of points in a Cartesian plane (x, y). The first is a set of base station test points (BTP), $BST_i = BST_1, BST_2, \ldots, BST_{N_{bts}}$ which represent the available set of base station sites acquired by the network service provider. The second set of points represent service test points (STP) which is a test point representing a user at which a minimum signal level must be received to ensure required quality service requirements are met, $STP_i = STP_1, STP_2, \ldots, STP_{N_{stp}}$, where N_{stp} is the number of test points. The threshold relationship can be defined as $P - PL \geq \gamma$, where P is the transmitted power, P_L is the path loss, and γ represents a threshold. A general strategy for solving the above problem using a genetic algorithm approach as shown in [67] is given in algorithm 6.

Algorithm 6 Determining Candidate Sties in Base Station Placement Problem

```
Initialise an area for Sites
Conduct Evaluation of Candidate Sites
while Best Sites Not Reached do
  Select a Number of Optimum Sites (x) from Candidate Sites
  Conduct Evaluation of Sites based on Fitness Criteria
  Conduct Extraction of A New Set of Candidate Sites equal to (c − x)
  Replace Candidate Sites by Removing Invalid Sites
  if Best Sites Reached then
    Exit
  end if
end while
```

As shown in [83], the following optimisation objectives may be identified:

1. Minimising the number of base station sites in the network which contributes to overall cost reduction of capital expenditure in the network roll out (CAPEX).

2. Maximising the coverage of the network by ensuring that every point in the service area is covered by a BTS with minimum signal strength (evaluation of validity of STP_i).

3. Reducing noise and interference in the network through optimal site location.

4. Maintaining the required Signal to Interference Noise Ratio (SINR) for each user at the receiver to ensure that the required QoS requirements to support a specific service is maintained.

In [83], the total fitness function for selection of individual i is given by

$$f_t(I) = w_1 f_1(I) + w_2 f_2(I), \tag{B.1}$$

where $f_1(I)$ is an objective function that is used to maximise the number of users covered by BTS_i while reducing the cost of the network in terms of total number of base stations used, $f_2(I)$ is the objective function that takes into account minimisation of the inter-cell interference and ensures that each user maintains a minimum SINR, w_1 and w_2 represent weighting factors which could take values between 0 and 1 such that $w_1 + w_2 = 1$ to favour coverage or interference minimisation [83]. An extension of the above work is considered in [55]. To deal with growth in demand for services which leads to poor QoS in the network, the addition of new Node Bs in the network could be considered as a solution for solving the need for additional capacity in the network. However, the site selection of the node Bs that need to be added to the network needs to be optimised. By classifying nodes as critical or non-critical in terms of impact on QoS in the network, a Tabu search algorithm is used to selectively *drop* node Bs without influencing the overall quality required in the network. Through this iterative process, reduced network deployment cost is achieved while maintaining required QoS in the network.

B.4 Conclusion

This appendix provided a brief overview of related work linked to capacity optimisation in mobile networks using combinatorial optimisation approaches. As stated previously, with the increase in problem size, the computational time of exact approaches can be highly compromised, and the use of heuristic approaches are recommended [90]. This appendix provides a contrast to the possible methods that could be used for optimisation of resources in mobile cellular networks.

Appendix C

Publications

The following research outputs were generated during this study. Outputs related to this study are also listed below. The following publications were published at local and international peer-reviewed conference:

1. AM Kurien, K Djouani, BJ Van Wyk, Y Hamam, A Mellouk, *Using Empirical Mode Decomposition for Subscriber Behaviour Analysis in Cellular Networks in South Africa*, 7th IEEE International Multi-Conference on Systems, Signals and Devices (SSD) 2010, June 27-30, Amman, Jordan.

2. AM Kurien, G Noel, A Mellouk, BJ Van Wyk, K Djouani, *Efficient Classification based on Multi-Scale Traffic Data Extraction Patterns of Cellular Networks*, 6th ACM International Wireless Communications and Mobile Computing Conference (IWCMC) 2010, June 28-July 3, Caen, France.

3. AM Kurien, BJ Van Wyk, Y Hamam, *Mining Time Series Data in Mobile Cellular Networks*, 3rd International Conference on Broadband Communications, Information Technology and Biomedical Applications (BroadCom'08), pp. 463-467, November 2008, Pretoria, South Africa, ISBN 978-0-7695-3453-4.

The following paper was published as a book chapter:

1. AM Kurien, BJ Van Wyk, Y Hamam, J Jordan, *The Use of Semi-Parametric Methods for Feature Extraction in Mobile Cellular Networks*, 8th International Conference on Intelligent Data Engineering and Automated Learning (IDEAL'08), LNCS 5326, pp. 290-297, November 2008, Daejeon, Korea. ISSN 0302-9743.

The following paper was published in the Elsevier Simulation, Modeling and Practice Theory journal (SIMPAT):

1. AM Kurien, G Noël, K Djouani, BJ Van Wyk, A Mellouk, *A subscriber classification approach for mobile cellular networks*, Simulation Modelling Practice and Theory 25, pp 17-35, 1569-190X, doi:10.1016/j.simpat. 2012.02.008.

The following paper has been submitted for review to the Springer Optimization and Engineering Journal (OPTE), January 2012:

1. AM Kurien, K Djouani, Y Hammam, BJ Van Wyk, A Mellouk, *A two-level optimisation approach for resource allocation in mobile cellular networks.*

The following peer-reviewed conference papers were published that are related to this study:

1. R.W. Juma, K. Djouani, A. Kurien, *A Mathematical approach for Capacity Enhancement in 3G Mobile Networks*, Southern Africa Telecommunication Networks and Applications Conference (SATNAC) 2011, 5-7 September 2011, East London, South Africa.

2. BR Philemon, A Kurien, Y Hamam, *Base Station Placement for Uneven Traffic in Cellular Networks using Genetic Algorithm*, 3rd IASTED African Conference on Modelling and Simulation (AFRICA MS 2010), 6-8th September, Gaborone,Botswana.

3. Z Joao, M Mzyece, A Kurien, *Matrix Decomposition Methods for the Improvement of Data Mining in Telecommunications*, 2009 IEEE 70th Vehicular Technology Conference (VTC) Fall, 20-23 September 2009, Anchorage, Alaska, USA.

4. BR Philemon, A Kurien, Y Hamam, *The Optimisation of Base Station Site Placement for Unevenly Distributed Traffic using a Genetic Algorithm*, IASTED International Conference on Modeling and Simulation (AfricaMS 2008), September 2008, Gaborone, Botswana.

5. J Munyaneza, BJ Van Wyk, A Kurien, *Optimisation of Antenna Placement in 3G Networks Using Genetic Algorithms*, 3rd International Conference on Broadband

Communications, Information Technology and Biomedical Applications (BroadCom'08), pp. 463-467, November 2008, Pretoria, South Africa, ISBN:978-0-7695-3453-4.

The following are related research outputs that were published prior to the start of this study:

1. AM Kurien, BJ Van Wyk, LW Snyman, D. Chatelain, *An Environment-Based Network Planning Tool*, 12th IEEE International Symposium on Electron Devices for Microwave and Opto-Electronic Applications (EDMO'2004), Berg-en-Dal, Kruger National Park, South Africa, November 2004.

2. AM Kurien, BJ Van Wyk, D Chatelain, *Adapting Cellular Network Planning for Developing Countries in Southern Africa*, IPET International Conference, TUT Pretoria, South Africa, September 2004.

3. AM Kurien, BJ Van Wyk, LW Snyman, D Chatelain, *Intelligent Network Planning of Mobile Networks for Southern Africa*, IEEE Africon Conference, Gaborone, Botswana, September 2004.

4. AM Kurien, BJ Van Wyk, LW Snyman, D Chatelain, *Intelligent Planning of Mobile Networks for Southern Africa*, EUROSIM Conference 2004, Special Session on Modelling and Simulation of Distributed Systems and Networks, Paris, France, September 2004.