ADDIS ABABA UNIVERSITY

SCHOOL OF GRADUATE STUDIES

SCHOOL OF INFORMATION SCIENCE

DATA MINING APPROACH TO ANALYZE MOBILE TELECOMMUNICATIONS NETWORK QUALITY OF SERVICE: THE CASE OF ETHIO-TELECOM

LULU DEYU

MAY 2014

SCHOOL OF GRADUATE STUDIES

SCHOOL OF INFORMATION SCIENCE

DATA MINING APPROACH TO ANALYZE MOBILE TELECOMMUNICATIONS NETWORK QUALITY OF SERVICE: THE CASE OF ETHIO-TELECOM

A Thesis Submitted to the School of Graduate Studies of Addis Ababa University in Partial Fulfillment of the Requirements for the Degree of Masters of Science in Information Science

BY

LULU DEYU

MAY 2014

ADDIS ABABA UNIVERSITY
SCHOOL OF GRADUATE STUDIES
SCHOOL OF INFORMATION SCIENCE

DATA MINING APPROACH TO ANALYZE MOBILE TELECOMMUNICATIONS NETWORK QUALITY OF SERVICE: THE CASE OF ETHIO-TELECOM

BY

LULU DEYU

Name and Signature of Members of the Examining Board

Name	**Title**	**Signature**	**Date**
Ato Getachew Jemaneh	**Advisor**	_____	_____
Dr. Martha Yifru	**Examiner**	_____	_____
Ato Michael Melese	**Chair person**	_____	_____

Acknowledgement

I gratefully acknowledge the support and guidance of my advisor Ato Getachew Jemaneh. I would not imagine completing this work without all his scholarly advices. I am deeply indebted to him for his critical readings and constructive comments. I would like also to express my gratitude to all my instructors whose contribution helped me to succeed on this study.

I would like to express my deep gratitude and appreciation to the ethio telecom Engineering as well as Operation and Maintenance departments, especially, Ato Ashagre Getenet and his mobile optimization team, Ato Gebru Kerse and his team for their dedicated support in my study.

Last but not least, my deepest thank goes to my family for their emotional support and encouragement.

Acronyms

2G	Second Generation
3G	Third Generations
3GPP	Third Generation Partnership Project
AGCH	Access grant channel
ARFF	Attribute Relation File Format
ANSI	American National Standards Institute
ARIB	Alliance of Radio Industries and Business
AUC	Authentication Centre
BCCH	Broadcast control channel
BSS	Base Station Subsystem
BTS	Base Transreceiver Station
CART	Classification and Regression Trees
CCCH	Common control channel
CCH	Control channels
CDMA	Code Division Multiple Access
CDR	Call Drop Rate
CRISP	CRoss-Industry Standard Process
CSR	Call Success Rate
CSSR	Call Set-Up Success Rate
DAMA	Demand -Assigned Multiple Access
CSV	Comma Separated Value
DCCH	Dedicated control channel
DNS	Domain Name Servers
EDGE	Enhanced Data rates in GSM Environment
EFY	Ethiopian Fiscal Year
EIR	Equipment Identity Registers
ETSI	European Telecommunication Standard Institute
FACCH	Fast associated dedicated control channel
FCCH	Frequency correction channel

FDMA	Frequency Division Multiple Access
FP-growth	Frequent Pattern growth
GGSN	Gateway GPRS Support Node
GPRS	General Packet Radio Service
GSM	Global Standard for Mobile Communication
HLR	Home Location Register
HOSR	Handover Success Rate
ICT	Information Communication Technology
IP	Internet Protocol
ISDN	Integrated Switch Digital Network
ITU	International Telecommunication Union
KDD	Knowledge Data Discovery
KPI	Key Performance Indicator
KQI	Key Quality Indicator
LAC	Location area code
LAPD	Link Access Protocol for D-channel
LTE	Long Term Evolution
MLP	Multi-Layer Perception
MSC	Mobile Switching Control
NMS	Network Management System
NP	Network Performance
NSS	Network Switching Subsystem
O&M	Operation and Maintenance
PCH	Paging Channel
PSTN	Public Switch Telephone Network
QoS	Quality of Service
RACH	Random access channel
RAN	Radio Access Network
RF	Radio Frequency
SACCH	Slow associated dedicated control channel
SCH	Synchronization channel

SDCCH	Stand-alone dedicated control channel
SGSN	Serving GPRS Support Node
SMS	Short Message Service
SMSC	Short Message Service Centre
SOM	Self-Organizing Map
SS	Spread Spectrum
SS7	Signaling system no. 7
TCH	Traffic channels
TCHCR	TCH Congestion Rate
TCSM	Transcoder sub-multiplexer
TMN	Telecom Management Network
TRX	Transceivers
TS	Time slots
UMTS	Universal Terrestrial Mobile System
VAS	Value Added Services
VAS IN	VAS INtelligent services
VLR	Visitor Location Register
VMS	Voice Mail System
WCDMA	Wide band Code Division Multiple Access

Table of Contents

List of Tables

List of Figures

Abstract

Huge amount of measurement data indicating the performance of a mobile network has been generated. Sometimes it is very difficult to draw essential information from this complex data merely applying domain expertise and prior knowledge. For the ultimate goal of QoS improvement, it is helpful to follow a data mining approach to deal with this complex data.

In this study, a sample data on three time stamps such as 24-hour, 1-month, and 1-week day and night high traffic hours, indicating QoS KPIs has been taken from the live network of ethio telecom. Strictly following the KDD process, various experiments are conducted using the Weka open source data mining tool. This is done to find out the number of clusters that logically segment the KPI data applying the simple k-means algorithm and the best classification model comparing the J48 decision tree, the Naïve Bayes, as well as the Multilayer Perception classifiers.

It has been found that the cluster model worth splits the KPI data in to five clusters on the basis of their natural proximity. These clusters are ranked and labeled to be applied on the next classification model experiment. In this experiment a data set of four selected attributes and 8478 instances has been used to build and select the best model. A separate data set of 4240 instances is provided to finally evaluate the classification accuracy of the selected model for unseen data. As a result a classification model built on Multilayer Perception with 6 ‘Hidden Layers’, ‘Learning Rate’ of 0.1 and ‘ Seed’ value of 2 has got the best classification accuracy by correctly classifying 84.4953 % of the data in to their classes.

Key Words: QoS, KPI, KDD process.

Chapter One

1. Introduction

1.1 Background

The application of data mining for any industry generally depends on the availability of data and business challenges that reside in the industry as described in Weiss (2009). In this regard, the telecommunications industry generates high quality data from its network operation and the occurrence of large customer that rely on the network infrastructure. Those data generated as a result of the business operation of telecommunications include phone call data regarding each call conducted by the customer in the form of call detail record, billing information that details about the payment to be discharged together with the customer profile, and data generated as a result of the network operations. On the other hand this telecom industry faces enormous business challenges such as how to improve the functionality of its market, how to detect and prevent fraudulent call activities, as well as how to plan and optimize the network and manage the recurring fault. Acting up on the routinely generated huge data, these business challenges can be resolved through the application of data mining.

There are also so many data mining challenges in applying the telecommunications data for data mining. As discussed in Weiss (2009) these challenges include the scale of the data in the large telecommunications database, the raw data needs to be summarized based on important features to make it suitable for data mining, predicting very rare events such as detecting a fraudulent call activity from the time series data that represent individual events, as well as many data mining models such as fraud detection and network fault isolation needs to be applied in real time.

Data mining technology solve problems through the analysis of data already exist in databases. As the observed data sets are grown in size and complexity there is a need to automatically analyze these data using data mining technology through the application of different intelligent algorithms such as neural networks, decision trees, association rules and others, Pitas et al (2011). When it comes to mobile network quality of service (QoS), the observational data for

performance measurement could be captured from the live network through drive test measurement or from the network management system database.

It is the user expectations that constitute the Quality of Service (QoS), which is defined as "the collective effect of service performances, which determine the degree of satisfaction of a user of the service" ITU-T E.800 (1988), pp. 3. This general definition means that a single QoS measure is not possible. In this regard, Hardy (2001) has specified three notions of QoS, which are intrinsic, perceived, and assessed quality of service. **Intrinsic quality** is achieved via the technical design of the transport network and terminations, which determine the characteristics of the connections made through the network, and provisioning of network accesses, terminations, and switch-to-switch links, which determines whether the network will have adequate capacity to handle the anticipated demand. **Perceived QoS** resulted from user experiences when a service is being used. **Assessed QoS** indicates the value of continued use of a service for the user who pays for it.

Suutarinen (1994) develop a solution for quality performance measurement to manage the performance of a GSM base station system and suggest a task oriented approach to network management which is classified in to four categories:

1. Implementation of a new network - the functionality of the network must be verified from base station sub-system if problems occur
2. Monitoring - daily evaluation and control of services.
3. Tuning - verifying adequate service levels, identifying problems, optimization, and analysis of the network.
4. Planning - optimal configuration of the network is a perpetual process.

Each task category must have defined goals and information criteria, and means must be developed to get the information from the network management system.

Mobile communication network that has passed through more than three generations is one of the communication technologies. The historical milestone shows that the first generation mobile networks were analog and entirely meant for voice communication. In the second generation though the switch was changed from analog to digital still it provides voice. However, the move from analog to digital produces some non-voice services such as Short Message Service (SMS).

The later development of General Packet Radio Service (GPRS) for Second Generation (2G) networks provided many mobile users with their first taste of mobile Internet services though more bandwidth would be needed to satisfy all users of this technology. 3G expanded the data delivery capabilities of GPRS to make mobile internet services truly mainstream, Mishra (2004).

In Ethiopia, mobile communication service dates back to 1999 and currently ethio telecom is the sole provider owned by the Federal Government of Ethiopia. ethio telecom has been established on November 2010 by the Council of Ministers Regulation No 197/2010 repelling the Ethiopian Telecommunications Corporation establishment Council of Ministers Regulation No. 10/1996, Federal Negarit Gazeta 17th (2011). The operator has passed through different names since 1894 at the governance of Emperor Menelik II when the 407 Km telegraph and telephone line between the cities of Harar and the capital Addis Ababa was constructed. The major services provided by this company includes: Fixed telephone (both wired and wireless), Internet and data (dialup and broadband), mobile (pre-paid and post-paid), CDMA and WCDMA (voice, internet and data), and other value-added services as stated in ethio telecom company profile (2012).

As described in the press release of November 28, 2013, ethio telecom has signed a 1.6 billion dollar telecom expansion project contract with Chinese companies, Huawei and ZTE, in order to realize the Government's Growth and Transformation Plan (GTP) in the telecom sector. The project contract would increase the mobile service capacity to 59 million and to implement in Addis Ababa the fourth generation (4G) service or LTE (Long Term Evolution) which is the modern technology. Through this contract, the country's telecom network total coverage will reach 85 %. So that by undertaking all-round and international standard telecom infrastructure deployment through this telecom expansion projects the company would increase the nationwide telecom infrastructure by more than double compared to the infrastructure deployed so far.

ethio telecom has the following objectives:

- Being a customer centric company
- Offering the best quality of services
- Meeting world-class standards
- Building a financially sound company

1.2 Statement of the problem

There are various tasks in telecommunications that demand the application of data mining techniques. These tasks include, but not limited to the detection of fraudulent call activities which is the identification of very rare events, customer relationship management (CRM) or customer profiling, and network management tasks where this study is categorized.

Huge amount of measurement data that indicate the performance of a GSM (Global System for Mobile communications) network and even more huge amount of data indicating all the alarm events in this infrastructure have been generated. Performance experts in the telecom domain, specifically in ethio telecom are expected to analyze the information in the measurements to manage and improve the quality of service (QoS). Sometimes it will be difficult to exhaustively produce essential information from this complex data by solely applying domain expertise and a prior knowledge as the performance experts do. It is here that the application of data mining methods to deal with this complex data to improve the quality of service becomes helpful.

Telecom operators often report the performance of their network quality in terms of key performance indicators (KPIs). There are so many KPIs to evaluate the quality of a mobile telecommunication network. These KPIs are designed to measure the quality of specific services such as voice, data, internet … etc. as well as the general quality of a mobile network. Although most of these KPIs are common for many telecom operators, some of them are different.

Very large amount of KPI data is often generated from the network management system of ethio telecom for the purpose of mobile network optimization. Engineers in the performance optimization task analyze these data based on their experience and prior knowledge. However, these data is so huge and complex that it cannot be easy to make an exhaustive extraction of important and relevant knowledge unless and other wise a better data analysis mechanism is implemented. Data mining is the best data analysis technique that can extract relevant and important knowledge from such a huge and complex data. This study will address the applicability of data mining techniques to analyze the mobile telecommunication network QoS based on these KPIs.

Pitas et. al. (2011) presents a paper entitled “QoS Mining Methods for Performance Estimation of Mobile Radio Networks” on the 10th International Conference on Measurement of Speech,

Audio and Video Quality in Networks. It is proved that quality of speech and video telephony services can be discovered applying algorithms like the k nearest-neighbor (KNN) classifier, decision trees and Multilayer Perception (MLP) on Weka data mining tool. The data set is built based up on data gathered from a drive test measurement. The result indicates that using KNN classifier; it is possible to achieve 62.13% classification accuracy for GSM Speech, 88.49% classification accuracy for UMTS Speech, and 77.56% classification accuracy for UMTS Video. Finally, the study concludes that learning from QoS measurements is suitable for building evaluation and prediction models. However, the classification accuracy achieved is not reliable for both speech and video qualities.

According to Weiss (2006), extensive amount of data is generated and stored in telecommunications companies regarding the operation of their networks. The network elements in the huge telecommunications network have self-diagnostic capabilities and generate both status and alarm messages. These streams of messages can be mined to support network management functions. However, the messages are generated based on conformance of a certain threshold point in reference with the measurement data which can also be mined.

On the other hand, in order to deal with the complex telecommunications network infrastructure, Liebowitz (1988) proposed an expert system that could capture knowledge from human experts in the telecommunication area. However developing the expert systems is not only time consuming but also it is difficult to get the necessary domain knowledge from the experts. Data mining can be considered as a mechanism to extract some of such knowledge from the relevant data.

The knowledge extracted from the huge KPI data as a result of data mining can benefit domain experts in the GSM performance optimization task being an additional knowledge to their prior experience. Moreover, this knowledge enables to produce effective utilization of network resources.

To the reach of the knowledge of the researcher, no local research has been conducted to solve the problem of data analysis in mobile telecommunication network QoS using data mining technique. Hence the purpose of this study is to analyze the QoS for mobile telecommunications network applying different data mining techniques using the relevant KPI data extracted from the

live ethio telecom network management system. In this regard, this study attempts to answer the following research questions:

- What number of clusters logically segments the KPI data?
- What most combinations of KPIs produce which level of QoS?
- Which data mining algorithm best classifies the KPI data in to the right level of QoS?

1.3 Objectives of the Study

1.3.1 General Objective

The general objective of this study is to develop a model for QoS analysis of a mobile network using data mining techniques.

1.3.2 Specific Objectives

- To study key components of a mobile network related to QoS.
- To collect KPI data indicating performance from live ethio telecom GSM network.
- To identify KPIs appropriate to evaluate the general quality of a mobile network.
- To construct a target data set following steps of the KDD process model
- To develop a data mining model for QoS analysis.
- To evaluate the proposed model.
- To draw recommendations based on the findings.

1.4 Scope of the Study

Although the QoS concept is the same in all the mobile communication technologies such as 2G, 2.5G, 3G, 4G, and others, due to the technological difference each generation would better be treated and studied separately. Thus, due to time limitation to cover each technology one by one and computational resource limitation to run the resulting data, the scope of this research work is limited to the general QoS for mobile communication networks of ethio telecom in Addis Ababa specifically the 2.5G, GSM network. Moreover, it is limited to the data mining aspects of clustering and classification using the proposed algorithms.

1.5 Significance of the Study

The huge and complex KPI data should be managed in order to explore and extract important knowledge from it. In this regard, the research will propose a data mining model to analyze the complex data generated from the live GSM network. The resulting knowledge is also important for effective network resource utilization.

1.6 Research Methodology

Primary and Secondary Sources: On this study review of different internal reports, manuals, interview of relevant professionals and observation of the actual system and other relevant data were undertaken. Moreover, extensive literature review has been conducted to identify and understand how other similar researchers deal with QoS related problems in a GSM network.

Data source: The raw data for this specific research are collected from the ethio telecom live mobile network. This data includes Key Performance Indicators (KPIs) that indicate the performance of a GSM network.

Process Model: The nine step KDD process described from the practical viewpoint proposed by Fayyad et al. (1996b) has been used in order to perform this study throughout the experimentation and analysis tasks. The steps in this process model are more clarified specially in preprocessing and data mining stages in detail than the CRISP (Cross Industry Standard Process) data mining process model. Other data mining process models such as 5A's (Assess, Access, Analyze, Act, Automate) proposed by SPSS or SEMMA (Sample, Explore, Modify, Model, and Assess) proposed by SAS are product specific. Moreover it refers to the overall process of discovering useful knowledge from data. It involves the evaluation and possibly interpretation of the patterns to make the decision of what qualifies as knowledge. It also includes the choice of encoding schemes, preprocessing, sampling and projections of the data before the data mining step, Mariscal, Marba, & Fernandez (2010). Thus, the steps in the KDD process model were well suited to deal with the problem at hand.

Tools: Weka open source data mining tool has been used in all the data mining aspects of this study. Updated version of this tool is often available with full documentation. Moreover it is not only the researcher's familiarity with the tool but also many of its features are well suited for the

data mining tasks of this study. Microsoft Excel was used for filtration of the data extracted in CSV format.

1.7 Expected Findings and Summary

This research will point out a better way on the analysis of a GSM network based on historical KPI data collected from the live ethio telecom network. Moreover what combination of KPIs will correspond to a specific ranked quality will be explored.

1.8 Organization of the Research

This study is organized in six chapters. The first chapter is the introduction part that introduces key points about the research including the background, the scope, the objectives and others. In chapter two, important technologies in the mobile telecommunications network related to network planning and optimization including a high level view of each generation mobile network technology will be presented. Chapter three contains the data mining knowledge and data mining processes in different literatures including those applied on this specific study as well as a literature review related to this study. Chapter four contains specific data mining algorithms that will be applied during the experiment to build a model. Chapter 5 contains the experiment and analysis part, where experimentation of all the algorithms indicated in chapter four will be conducted in order to build a model and give analysis. Finally, conclusions and recommendations based on the study will be provided in chapter 6.

Chapter Two

2 Mobile Cellular Network and Quality of Service

2.1 Overview of Mobile Communication in Ethiopia and the World

As mobile cellular network is among the rapidly growing telecommunication technologies, operators in the telecom industry should keep abreast of this growth in order to satisfy the fast growing subscription. According to the ITU World Telecommunication/ICT Indicators database, mobile cellular subscription increases from 2,205 million in the year 2005 to 6,835 million in 2013 worldwide.

Year	2005	2006	2007	2008	2009	2010	2011	2012	2013
Growth (millions)	2205	2745	3368	4030	4640	5320	5962	6411	6835

Table 2.1 Mobile Cellular Subscription Growth World Wide (Summarized from ITU World Telecommunication/ICT Indicators database)

Mobile service in Ethiopia has existed since 1999 and at that time the network coverage was limited to Addis Ababa with a network capacity not more than 60,000 subscribers, Gebremeskal (2006). In ethio telecom press release of September 09, 2011, it is described that the GSM and WCDMA network capacity has increased from 8,762,047 at the end of 2010 to a total of 18,408,780 at the end of 2011. And the total customer base compared with the previous year has shown 45.8% increase. The remarkable increment has been shown in GSM subscription, which is 57.63%. The international global link capacity has been expanded to 5.57 Gb/s.

As described in September 18, 2012 press release, the subscription of mobile reached 17.26 million at the end of 2011. The total customer base as of June 2012 has shown 59% increment when compared with the last fiscal year, out of which the growth rate of GSM is more than 64%. The total revenue secured in this year was 2.35 billion Birr, out of this GSM revenue accounted for 66.6%. These figures show that mobile communication is growing in its infrastructure, subscription, and revenue drastically from year to year.

2.2 Standardization Bodies in Mobile Technology

The major standardization bodies that play an important role in defining the specifications for the mobile technology as discussed in Mishra (2004) are:

- ITU (International Telecommunication Union): The ITU, with headquarters in Geneva, Switzerland, is an international organization within the United Nations, where global telecom networks and services are coordinated in governments and the private sector. The ITU-T is one of the three sectors of ITU and produces the quality standards covering all the fields of telecommunications.
- ETSI (European Telecommunication Standard Institute): This body was primarily responsible for the development of the specifications for the GSM. Owing to the technical and commercial success of the GSM, this body will also play an important role in the development of third-generation mobile systems. ETSI mainly develops the telecommunication standards throughout Europe and beyond.
- ARIB (Alliance of Radio Industries and Business): This body is predominant in the Australasian region and is playing an important role in the development of third-generation mobile systems. ARIB basically serves as a standards developing organization for radio technology.
- ANSI (American National Standards Institute): ANSI currently provides a forum for over 270 ANSI-accredited standards developers representing approximately 200 distinct organizations in the private and public sectors. This body has been responsible for the standards development for the American networks.
- 3GPP (Third Generation Partnership Project): This body was created to maintain overall control of the specification design and process for third-generation networks. The result of the 3GPP work is a complete set of specifications that will maintain the global nature of the 3G networks.

2.3 Evolution of Mobile Network

The evolution of mobile network as briefly discussed in Mishra (2004) is categorized into different ‘generations’ as shown in Figure 2.1. Overview of each generation is given below

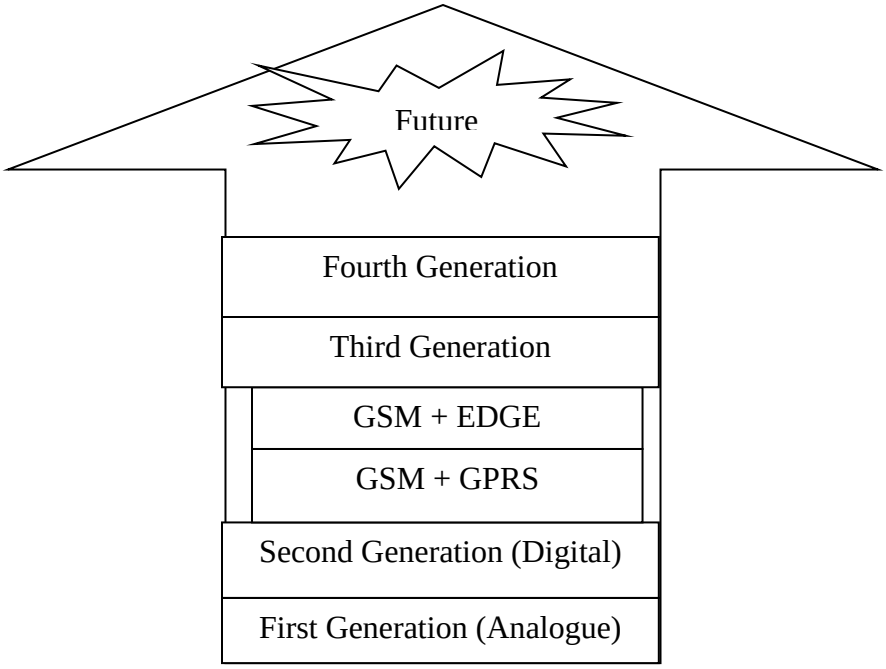


Figure 2.1 Evolution of Mobile Network (Source: Mishra (2004))

2.3.1 The First-generation System (Analogue)

The first-generation mobile system which is based on analogue transmission techniques was started in the 1980s. The frequency spectrum was not efficiently utilized and Roaming service is not implemented. At that time, there was no worldwide coordinating body to develop technical standards for the system. Nordic countries deployed Nordic Mobile Telephones or NMTs, while UK and Ireland went for Total Access Communication System or TACS, and so on.

2.3.2 The Second-generation System (Digital)

In the mid-1980s the European commission started to liberalize the communications sector including mobile communications as a result ETSI, the standardization body in Europe, was established and launch the first specification. At the beginning of 1991, digital technology called Global System for Mobile Communication or GSM was implemented in the network of this generation. GSM has gradually evolved to meet the requirements of data traffic and other services.

- GSM and VAS (Value Added Service): Two VASs called Voice Mail System (VMS) and the Short Message Service Centre (SMSC) were added in the GSM system. In some networks SMS traffic constitutes a major part of the total traffic as a result SMSC was

commercially successful. IN (Intelligent) services are also emerged and made fraud management and 'pre-paid' services to be created.

- GSM and GPRS (General Packet Radio Services): SGSN (Serving GPRS Support Node) and GGSN (Gateway GPRS Support Node) were added to the existing GSM system to send packet data on the air-interface. Part of the network handling the packet data is called the 'packet core network'. This network also contains the IP routers, firewall servers and DNS (domain name servers) in addition to the SGSN and GGSN. This enables wireless access to the Internet and the bit rate reaching to 150 kbps optimally.
- GSM and EDGE (Enhanced Data rates in GSM Environment): The need to increase the data rate in the data traffic was done by using more sophisticated coding methods over the Internet and thus increasing the data rate up to 384 kbps.

2.3.3 Third-generation Networks (WCDMA in UMTS)

Though high volume movement of data was possible in EDGE, still the packet transfer on the air interface work like a circuit switches call, which results in loss of packet connection in the circuit switch environment. The inconsistency of network standards around the world was also another challenge. Hence, it was decided to have a network its design standards are the same globally and provides services irrespective of technology platform. Thus, 3G also called UMTS (Universal Terrestrial Mobile System) in Europe, which is ETSI-driven, was born. IMT-2000 is the ITU-T name for the 3G system. WCDMA is the air-interface technology for the UMTS. The main components include BS (base station) or node B, RNC (radio network controller) apart from WMSC (wideband CDMA mobile switching center) and SGSN/GGSN. This platform offers many Internet based services, along with video phoning, imaging, etc.

2.3.4 Fourth-generation Networks (All-IP)

The fundamental reason for the transition to the All-IP is to have a common platform for all the technologies that have been developed so far, and to harmonize with user expectations of the many services to be provided. The fundamental difference between the GSM/3G and All-IP is that the functionality of the RNC and BSC is now distributed to the BTS and a set of servers and gateways. This means that this network will be less expensive and data transfer will be much faster.

2.4 Multiple-access Techniques

According to Horak (2007), communication networks adopt the concept of DAMA (Demand - Assigned Multiple Access). DAMA enables multiple devices to share access to the same network on a demand basis, that is, first come, first served. There exist a number of techniques for providing multiple accesses (i.e., access to multiple users) in a wireless network. Those techniques generally, but not always, are mutually exclusive.

Frequency division is the starting point for all wireless communications because all communications within a given cell must be separated by frequency to avoid mutual interference. Frequency Division Multiple Access (FDMA) divides the assigned frequency range into multiple frequency channels to support multiple conversations. Analog cellular systems employ FDMA. As discussed in Mishra (2004) the advantage of the FDMA system is that transmission can be without coordination or synchronization and its constraint is the limited availability of frequencies.

As mobile communications moved on to the second generation, FDMA was not considered an effective way for frequency utilization, so time division multiple access (TDMA) was introduced. TDMA is a digital technique that divides each frequency channel into multiple time slots, each time slot supports an individual conversation Horak (2007); Mishra (2004).

Code Division Multiple Access (CDMA) is relatively new technology, initially developed for military applications, has better bandwidth and service quality in congestion and interference environment. In this technology, every user is assigned a separate code/s depending on the transaction. One user may have several codes, thus, separation is based on codes than frequency or time. These codes are very long sequences of bits having a higher bit rate than the original information. The major advantage of using CDMA is that no plan is needed for frequency re-use, greater number of channels, effective utilization of bandwidth, and the confidentiality of information is well protected Horak (2007); Mishra (2004).

2.5 System Capacity

According to Dunlop and Smith (2000), the capacity of a system may be described in terms of the number of available channels or the number of subscribers that the system will support. The latter measure assumes that each call has a mean duration and not all of the subscribers will be

trying to make a call concurrently. Thus, it is the capacity planning undertaken from the outset that determines the system capacity. In this regard, Mishra (2004) identifies three essential parameters required for capacity planning: Estimated traffic, Average antenna height, and Frequency usage described in short hear after:

2.5.1 Traffic Estimates

Experience developed from studying an existing network and theoretical baselines are crucial for traffic estimates. Traffic in the network is dependent on two variables: the user communication rate, which is the amount of traffic generated by the subscriber per unit time and the user movement, which estimates the dynamic and static mode of network usage. The traffic on this network is estimated in terms of 'erlangs'. One erlang (1Erl) is equivalent to the utilization of a traffic channel for an hour. Considering that subscribers are speaking for 120 seconds on average, it is assumed that they will generate 25 mErl of traffic during busy hours. In some networks this figure will be 35 mErl and 90 s respectively.

The modulated stream of bits is sent in bursts having a finite duration. These bursts are generally called time slots (TS); the slots have a width of about 200 kHz. In the GSM system this is known as one time slot. There are eight time slots that can be used for sending the traffic and the signaling information. A typical time-slot composition is shown in Figure 2.2.

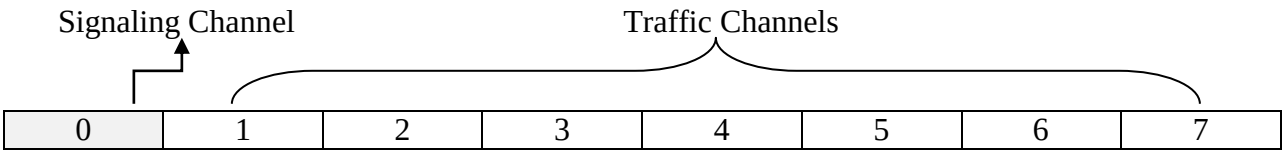


Figure 2.2 Time slot configuration for single TRX (Source: Mishra (2004)

Signaling requires one time slot (e.g. TS 0), and the remaining seven time slots (TS 1 to 7) can be used for traffic. In this configuration, the number of subscribers who can talk simultaneously is seven

2.5.2 Average Antenna Height

The average antenna height determines the basis of the cellular environment (i.e. whether it is macro-cellular or micro-cellular) and the frequency re-use pattern. The average antenna height is directly proportional to the covered area. In the case of micro-cellular environment where the

antenna height is low, there is an increase in the number of times the same frequency can be re-allocated and this will lead to the creation of more cells. The opposite is the case in a macro-cellular environment where the same frequency can be reallocated fewer times and the coverage area would be more. These relations are based on the interference analysis of the system as well as the topography and propagation conditions.

2.5.3 Frequency Usage and Re-use

Frequency usage is a concept related to both coverage and capacity usage and frequency re-use means how often a frequency can be re-used in the network. According to Dunlop and Smith (2000), the total number of voice channels depends on the radio spectrum allocated and the bandwidth of each channel. Based on this number a frequency reuse pattern must be developed in order to optimally use the channels and this is closely linked with cell size. The following are among the factors that decide the minimum distance where the same frequencies to be re-used:

i. The number of co-channel cells in the vicinity of the center cell;
ii. The geography of the terrain;
iii. The antenna height;
iv. The transmitted power within each cell

2.6 Constituents of Mobile Networks

Mishra (2004) provides a detailed description about the constituents of a mobile network on each generation. A condensed description of the 2G, 3G, and 4G is given in the coming paragraphs. Interested reader may refer this text to have a detailed knowledge on this area.

2.6.1 Second Generation Network

Out of the second-generation mobile systems, GSM is the most widely used. It is divided into three major parts: base station subsystem, network subsystem, and network management system as shown in Figure 2.3.

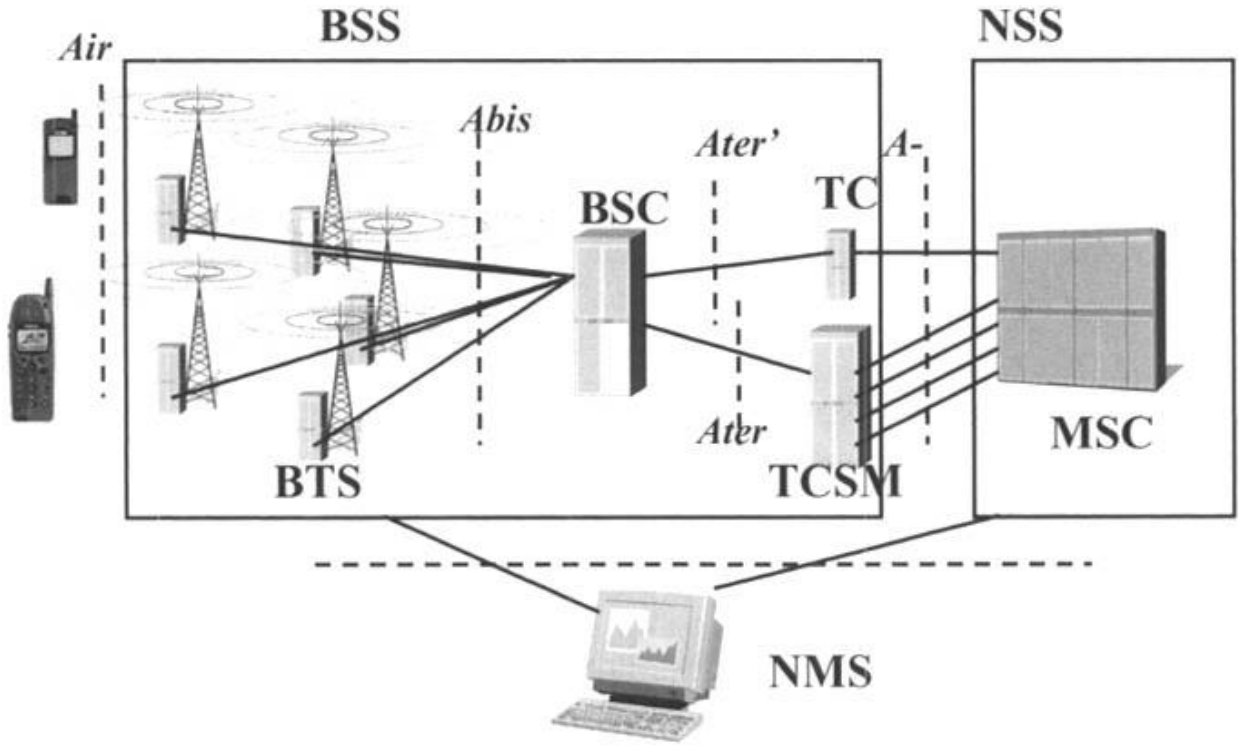


Figure 2.3 GSM architecture (Source: Mishra (2004))

The BSS consists of the base trans-receiver station (BTS), base station controller (BSC) and transcoder sub-multiplexer (TCSM). BTS manages the interface between the network and the mobile station. The major functions of the base station are transmission of signals in the desired format, coding and decoding of the signals, countering the effects of multi-path transmission by using equalization algorithms, encryption of the data streams, measurements of quality and received signal power, and operation and management of the base station equipment itself. On the other hand controls the radio subsystem, especially the base stations. The major functions of the BSC include management of the radio resources and handover, control transmitted power, and manages the operation and maintenance and its signaling, security configurations and alarms.

The network subsystem acts as an interface between the GSM network and the public networks, PSTN/ISDN. The main components of the NSS are MSC, HLR, VLR, AUC, and EIR. MSC is responsible for the switching functions that are necessary for interconnections between mobile users and other mobile and fixed network users. The HLR contains the information related to each mobile subscriber whereas the VLR comes into action once the subscriber enters the

coverage region and it is dynamic in nature. The AUC (or AC) is responsible for controlling actions in the network. The EIR contains the International Mobile Equipment Identity (IMEI) list of authorized numbers and allows the IMEI to be verified. Finally the NMS has four major tasks to perform: network monitoring, network development, network measurements, and fault management.

2.6.2 Third Generation Network

The three major parts in 3G networks are: the radio access network (RAN), the core network (CN), and the Network Management system (NMS) as shown in Figure 2.4.

The RAN further subdivided in to Radio Network Controller (RNC) and Base Station (BS) which are the radio and transmission components of the 3G system. The main functions of the BS include channel coding, interleaving, rate adaptation, spreading, etc., along with processing of the air-interface. And that of RNC involves load and congestion control of the cells, admission control and code allocation, routing of the data between the Iub and Iur interfaces etc.

The core network in 3G networks consists of two domains: a circuit-switched (CS) domain and a packet-switched (PS) domain. The CS part handles the real-time traffic and the PS part handles the other traffic. Both these domains are connected to other networks (e.g. CS to the PSTN, and PS to the public IP network). Major elements of the CN are WMSC/VLR, HLR, MGW (media gateway) on the CS side, and SGSN (serving GPRS support node) and GGSN (gateway GPRS support node) on the PS side.

The NMS in 3G systems is capable of managing packet-switched data and expected to handle both the multi-technology (i.e. 2G to 3G) and multi-vendor environments.

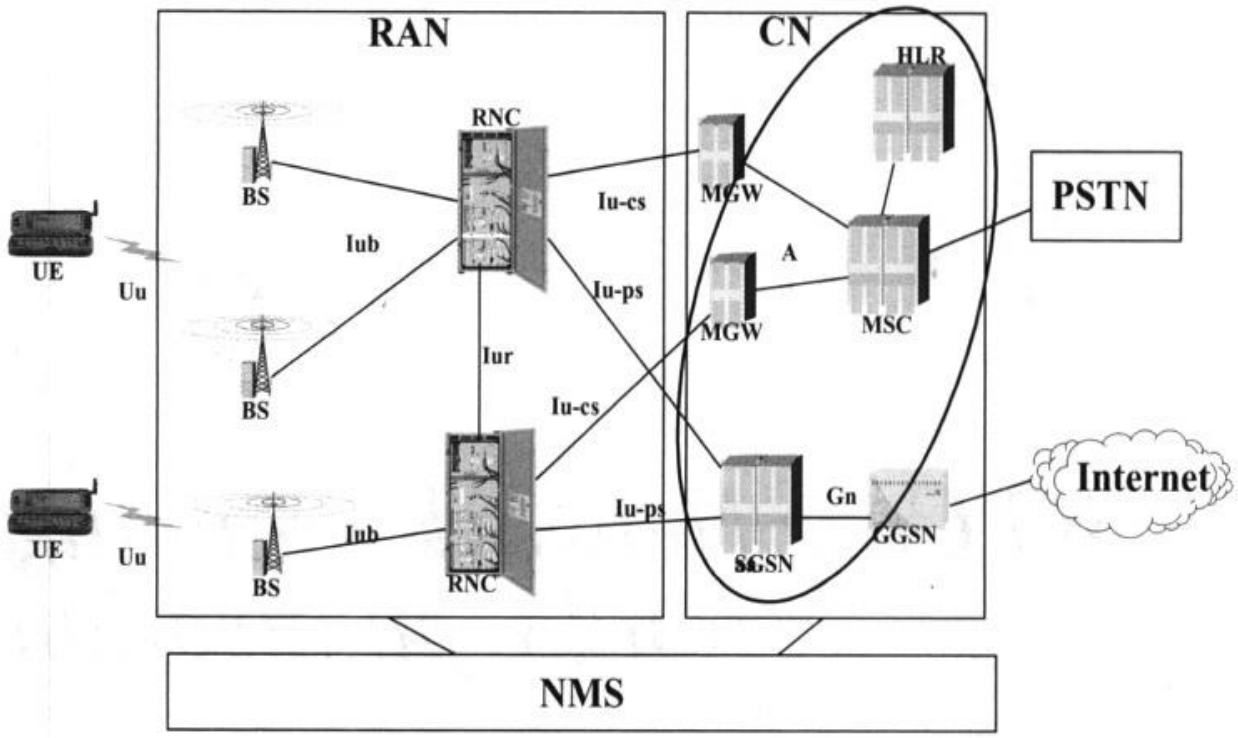


Figure 2.4 Third generation system (WCDMA) (Source: Mishra (2004))

2.6.3 Fourth Generation (All IP) Network

The difference between the All-IP network and the existing 2G and 3G networks is in the functionality of the RNC and BSC, which is now distributed to the BTS and a set of servers and gateways. Figure 2.5 indicates various elements in All IP network.

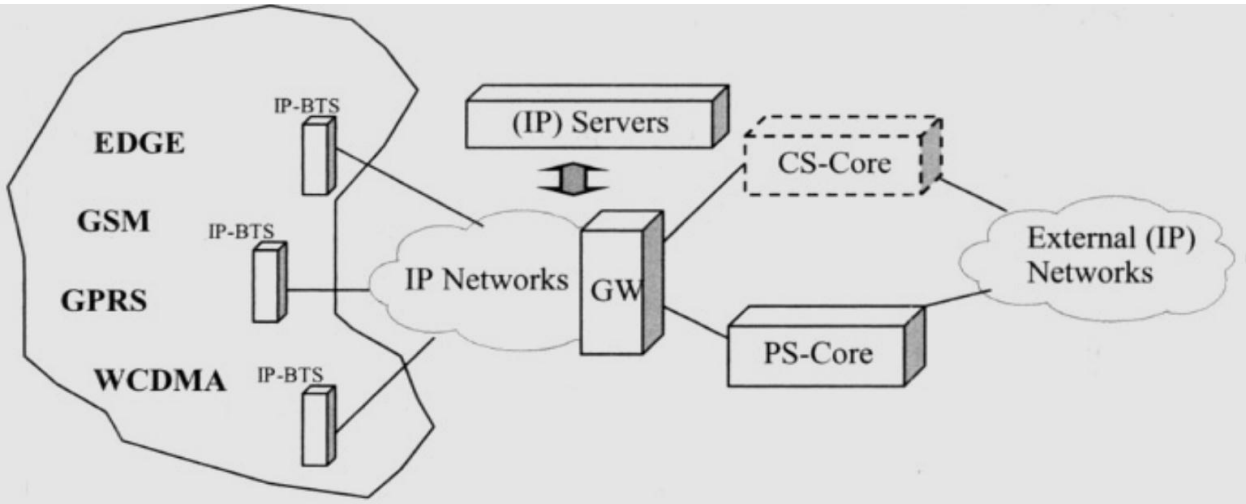


Figure 2.5 Example of an All IP Network (Source: Mishra (2004))

IP-BTS: The functionality of the IP BTS in this network is more than the functionality of base stations seen in the earlier generations; it acts as a mini-RNC/BSC.

(IP) servers: The IP BTS is not capable of performing all the RNC/BSC functions, which are of network level. These servers handle the signaling between the network elements.

Gateways (GW): These are responsible for the interaction of the IP-RAN and IP-Core networks. They are usually of two types, CS-GW and PS-GW; based on the type of call (circuit-switched or packet-switched) it is capable of handling. Table 2.2 compares 3G and 4G technologies.

Key Features	**3G Networks**	**4G Networks**
Data rate	384 Kbps to 2 Mbps	20 – 100 Mbps
Frequency band	1.8-2.4 GHz	2-8 GHz
Bandwidth	5 MHz	About 100 MHz
Switching technique	Circuit- and packet-switched	Completely digital with packet voice
Radio access technology	WCDMA, CDMA-2000 etc.	OFDMA, MC-CDMA etc.
IP	IPv4.0, IPv5.0, IPv6.0	IPv6.0

Table 2.2 Comparison of 3G and 4G network technologies (Source: Mishra (2004))

2.7 Telecommunications Management Network (TMN)

The communications industry has incorporated the Telecommunications Management Network (TMN) model to manage the business of a service provider as indicated in the TeleManagement Forum (2000). TMN is a reference model that specifies a set of management layers that build on top of each other and address different abstractions of the management space as illustrated in Figure 2.6, Clemm (2007).

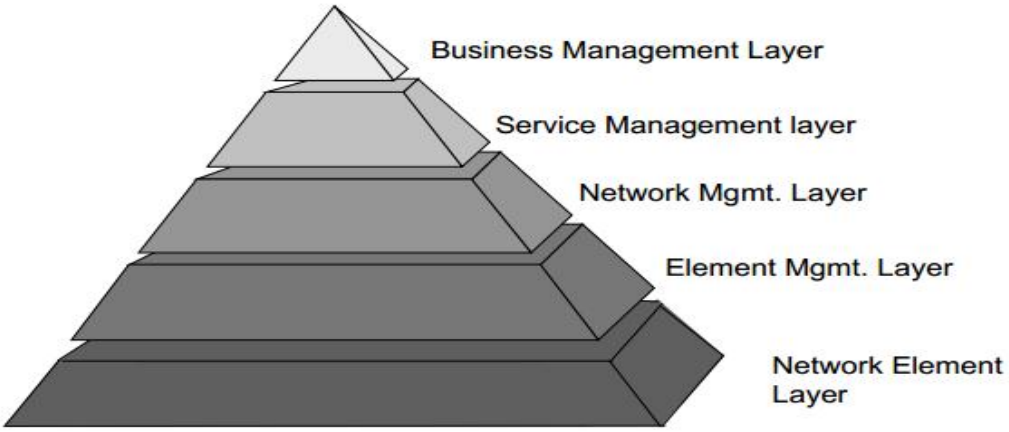


Figure 2.6 Basic TMN Layers (Source: TeleManagement Forum (2000))

The TMN model is simple, although its implementation is complex. TMN Management Functions covered in ITU-T Recommendation M.3400 (2000), provides a structure and decomposition of functions for all of the layers, TeleManagement Forum (2000). TMN management function sets available in this recommendation are classified into the following Management Functional Areas (MFAs), abbreviated as FCAPS:

- Fault Management: alarm surveillance, testing, and trouble administration
- Configuration Management: Parameter, provisioning, rating
- Accounting Management: Rating and billing
- Performance Management: Monitoring the QoS, traffic control
- Security Management: Managing access and authentication

On the basis of the above classification, Clemm (2007) redraw the TMN pyramid on Figure 2.6 with more refinement, as in Figure 2.7, to show the functional dimension in addition to the layering. ITU-T M.3010 defines applicability of this approach to TMN principles and architecture

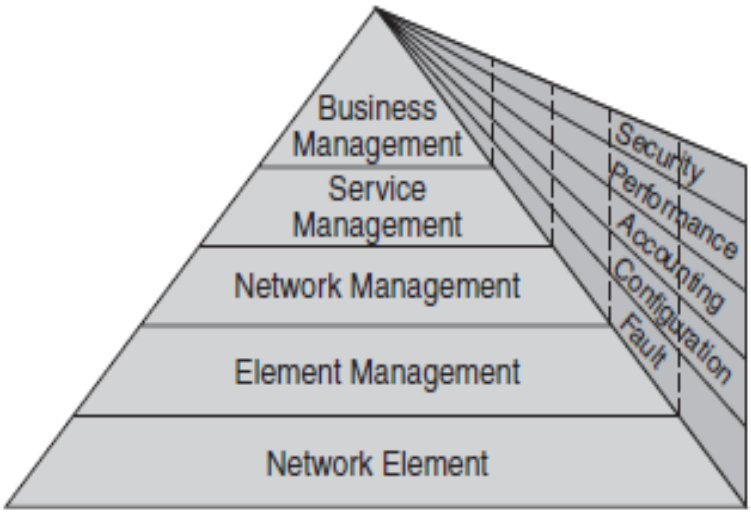


Figure 2.7 TMN Reference Model Refined with FCAPS (Source: Clemm (2007))

2.8 Quality of Service (QoS) and Network Performance (NP)

Quality of Service is the measure of service quality defined for a service and provided to a customer. Quality of Service is the definition of the performance parameters used to assess service quality. The parameters are usually associated with a specific service or service type. Quality of service is an important commercial issue for any telecommunication service. The network QoS is ultimately concerned with the quality of the communication service as perceived by the end-user. Therefore, the significance of network QoS is on an end-to-end basis, between the communicating entities, TeleManagement Forum (2000); Rahnema (2008).

According to ITU-CCITT E.800 (2007) network performance is the ability of a network or portion of a network to provide the functions related to communications between users. Network performance contributes to serveability performance and service integrity as shown in Figure 2.8. The contribution of the Organization to the QoS is characterized by one performance concept - service support performance, as shown in Figure 2.9. And the contribution of the network to the quality of service is characterized by three performance concepts, these are:

- Service operability performance, the ease by which the service can be used, including the characteristics of terminal equipment, the intelligibility of tones and messages, etc.

- Serveability performance, the ability of a service to be obtained within a specified condition when requested by the user and continue to be provided for the requested duration.
- Service integrity, the degree to which a service is provided without excessive impairments, once obtained. Thus, service integrity is primarily concerned with the level of reproduction of the transmitted signal at the receiving end.

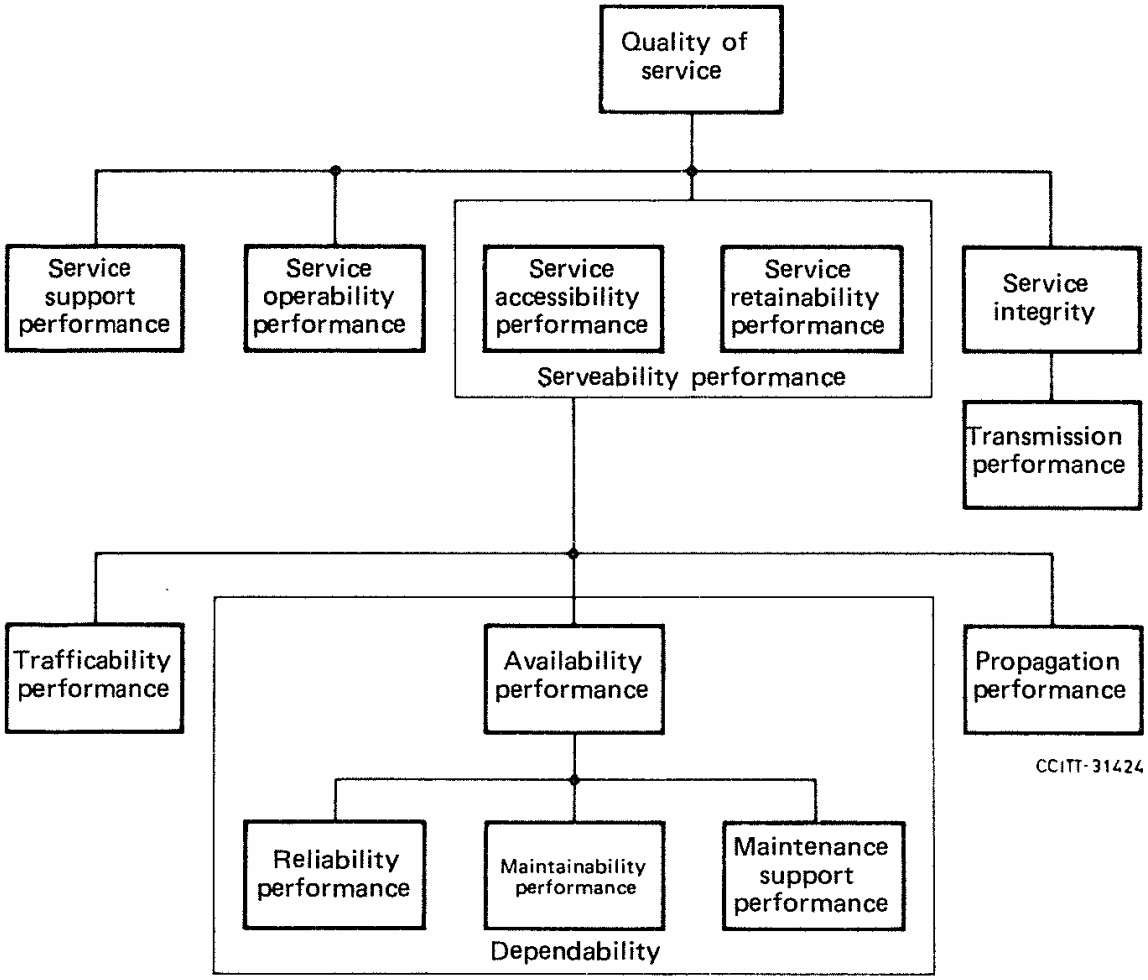


Figure 2.8 Performance concepts (Source: CCITT Recommendation E.800 (2007))

The relationship between QoS and NP is usually not a simple one and it is difficult to determine the range of each NP parameter producing any particular desired QoS level. Most often, several sets of NP parameters lead to an acceptable QoS, Rahnema (2008).

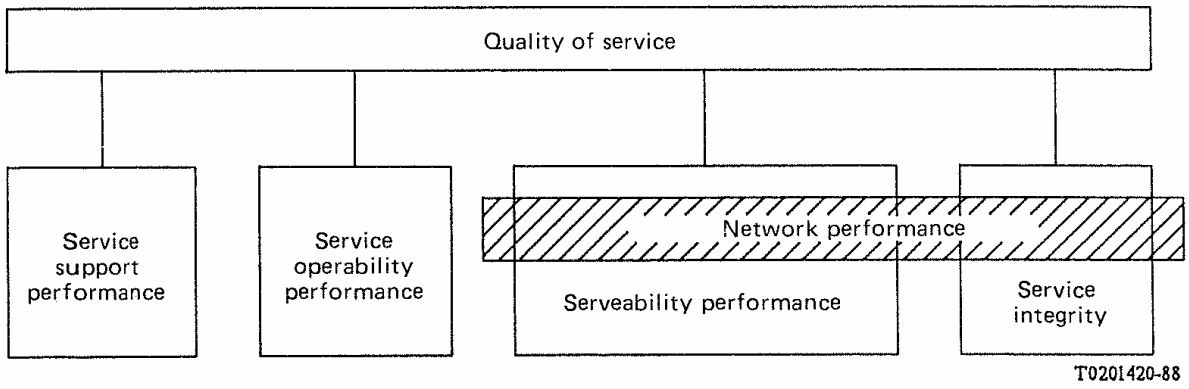


Figure 2.9 Relationships between QoS and NP (Source: CCITT Recommendation E.800 (2007))

2.9 Radio Access Network Key Performance Indicators (RAN KPIs)

Telecom operators have reported the performance of their networks against a set of KPIs. These KPIs are inherently network focused and they provide an indication of the end-to-end service delivery that the network supports. As indicated in Laiho, Wacker, and Novosad (2006), KPIs are an important measurement for network operations and will continue to be so for the foreseeable future. Two possible reasons are stated in ETSI TS 102 250-6 V1.2.1 (2004) for a parameter to be identified as a KPI. Either this KPI is a function aggregation of different parameters or it represents a very important quality measure related to the customer's perspective

The Radio Access Network (RAN) plays a prominent role in overall system performance, because it typically represents the bottleneck in terms of available transmission resources and capacity on the air interface. The RAN performance and its impact on user perception of the service quality are evaluated through a number of KPIs. Certain KPIs are defined to assess and evaluate end-user perception of the service quality. For voice calls, for instance, the main KPIs include the call set up success rate or network accessibility, call drop rate or service retainability, call set up delays, and voice quality or integrity, Rahnema (2008).

Lempiäinen and Manninen (2002) indicate the need for key performance indicators (KPI) not only to measure cost-efficiency and QoS of the radio network but also to show the planning areas where assessment is needed. The radio network cost-efficiency can be observed by measuring the effective usage of the network and frequency bandwidth and by defining certain KPI values to evaluate these topics. Moreover, a good radio network QoS requires high call success rate,

good voice quality and normal call release. In order to analyze the radio QoS, the KPI values such as call success rate, handover success rate, dropped call rate and blocking have to be measured.

The performance of cellular networks is crucial for telecom operators as their main goal is to keep the subscribers satisfied with the QoS they provide. To achieve the best performance, they have to monitor and analyze their network continuously. RAN KPIs are among the reports generated by the network and analyzed to optimize QoS. These raw data are available on the Network Management System (NMS) on-line database, Kyriazakos and Karetsos (2004), The KPI data undertaken for this specific research would be extracted from the NMS database of the operational mobile network of ethio telecom.

2.9.1 Logical Channels

Logical channels occur through the allocation of time slots by physical channels. Consequently the data of a logical channel is transmitted in the corresponding time slots of the physical channel. During this process, logical channels can occupy a part of the physical channel or even the entire channel. The GSM recommendations define several logical channels for signaling on the basis of this principle, dividing them into two main groups: traffic channels and control channels, as described in Kyriazakos and Karetsos (2004):

Traffic channels (TCH) are logical channels over which user information are exchanged between mobile users during a connection. Speech and data are digitally transmitted on these channels using different coding methods. It includes full rate traffic channel and half rate traffic channel.

Control channels (CCH): Control information is used for signaling and for system control. Typical signaling tasks include the signaling for establishing, maintaining and releasing traffic channels, for mobility management and access control to radio channels. Control information is transmitted over so-called control channels (CCH). Three groups of control channels were defined in GSM:

- Broadcast control channel (BCCH) which includes frequency correction channel (FCCH) and synchronization channel (SCH) as a sub class.

- Common control channel (CCCH) which includes Paging channel (PCH), Random access channel (RACH), and Access grant channel (AGCH) as a sub class.
- Dedicated control channel (DCCH) which includes Stand-alone dedicated control channel (SDCCH), Slow associated dedicated control channel (SACCH), and Fast associated dedicated control channel (FACCH) as a sub class.

Kyriazakos et al. find out that the logical channels that are primarily used in todays, mainly, voice traffic in cellular networks are the TCH (Traffic Channel) and the SDCCH (Stand-alone dedicated control channel) often referred as signaling channel. This paper also focuses on the KPI data of these two logical channels and handover.

2.9.2 Performance Measurement

As stated in Gómez and Sánchez (2005), performance measurement in the telecom world is usually defined in terms of accessibility, retainability and quality. Accessibility can be defined with the blocked calls, retainability with the dropped calls, and the quality with speech frame error rate. All these measured can be taken at the radio level (i.e. BSS) and easily translated into service quality.

2.9.2.1 Accessibility

As discussed in Ali, Shehzad, and Akram (2010); Gómez and Sánchez (2005), service accessibility or simply accessibility covers the user capability to access a service or radio resources within specified tolerances and other given conditions, i.e. call set-up or data channel assignment. This can be represented by the following equation:

$$Acessibility = \frac{Total\_NO\_of\_Successfull\_Calls\_Setup}{Total\_Calls\_Accesses\_to\_Network}$$

Listed below are the KPIs related to accessibility and only relevant to this research.

Standalone Dedicated Control Channel (SDCCH) Drop Rate: The SDCCH drop rate statistic compares the total number of Radio Frequency (RF) losses while using an SDCCH, as a percentage of the total number of call attempts for SDCCH channels. This statistic indicates that how good the cell/system is at preserving calls, Ali et al. (2010). This can be represented by the following equation:

$$SDCCH\_Drop\_Rate = \frac{SDCCH\_Drops}{SDCCH\_Seizures}$$

Possible reasons for SDCCH RF Loss Rate could be:

- Low Signal Strength on Down or Uplink
- Poor Quality on Down or Uplink
- Too High Timing Advance
- Congestion on Traffic Channel (TCH)

Call Set-Up Success Rate (CSSR): Rate of call attempts until TCH successful assignment. The Call Setup success rate measures successful TCH Assignments of total number of TCH assignment attempts, Haider et. al. (2009); Ali et al. (2010). In terms of equation:

CSSR = (1-SDCCH_Congestion_Rate) + TCH_Assignment_Success_Rate

Haider et. al. (2009) also point out the causes that CSSR might be affected and degraded:

- Radio interface congestion.
- Lack of radio resources allocation (for instance: SDCCH).
- Increase in radio traffic in inbound network.
- Faulty BSS Hardware
- Access network Transmission limitations (For instance: abis expansion restrictions)

Ali et. al. (2010), also describes reasons for low call setup success rate could be: TCH congestion, Interference, Poor coverage, and Faulty hard ware units. And also Popoola et. al. (2009) points out that it is easier is to set up a call as the value of CSSR becomes higher.

TCH Congestion Rate (TCH-CR): It is the first level of congestion experienced by the customer. As this value becomes higher, it would be difficult to make a call. It is the rate of blocked calls due to resource unavailability, Popoola et. al. (2009); Haider et. al. (2009). It can be represented by the following equation:

TCH Congestion = Number of calls blocked due to resource unavailable ÷ Total number of requests.

According to Haider et. al. (2009), TCH-CR values might arise due to following issues:

- TRX hardware faults
- Higher number of subscribers and/or traffic in a certain area.
- Lesser capacity sites (mainly due to hardware resource unavailability).

Ali et. al. (2010), also describes possible reasons for call setup block could be: Increasing Traffic Demand, Bad Dimensioning, HW Fault & Installation Fault, High Antenna Position, Low Handover Activity, and Congestion in Surrounding Cells.

2.9.2.2 Retainability

Service retainability covers the ability to keep up a call or the data channels in a packet-switched system. In other words, it is the ability of a service, once obtained, to continue to be provided under given conditions for a requested duration, Ali et. al. (2010); Gómez and Sánchez (2005). This can be expressed by the following equation:

$$Retainability = \frac{Total\_Calls\_Completed}{Total\_Successful\_calls\_setup}$$

Listed below are the KPIs connected to retainability and only relevant to this research.

Call Drop Rate (CDR): CDR measures the network ability to retain call conversation once it has been established or set up. It is the Percent of TCH dropped after TCH assignment complete as discussed in Popoola et. al. (2009). In terms of equation:

CDR = Number of TCH drops after assignment ÷ Total number of TCH assignments.

According to Haider et. al. (2009), CDR might arise due to following issues:

- External or internal interference over the air interface; Internal interference corresponds to in-band (900/1800 MHz) while external interference corresponds to other wireless (usually military) networks.
- Coverage limitation.
- Hardware faults (such as BTS transceiver, which is a part of BSS failures).
- Missing adjacencies (definition in BSS/OMCR).

Ali et. al. (2010), also describes some possible reasons for TCH-DCR could be: low signal strength on down or uplink, lack of best server, congestion in neighboring cells, battery flaw, poor quality on down or uplink, too high timing advance, antenna problems, low BTS output power, missing neighboring cell definitions, unsuccessful outgoing and incoming handover.

Handover Success Rate (HOSR): The handover success rate shows the percentage of successful handovers of all handover attempts. A handover attempt is when a handover command is sent to the mobile, Ali et. al. (2010). In other words, it is the rate of successful handovers (intercell + intracell). In terms of equation:

HOSR = No of successful [intercell + intracell] HO Attempt ÷Total number of HO requests.

Haider et. al. (2009) discuss the issues that HOSR might be affected as:

- Interference (either external or internal) over the air interface.
- Missing adjacencies.
- Hardware faults (such as BTS transceiver, which is a part of BSS failures).
- Location area code (LAC) boundaries wrongly planned and/or defined (where Location area represents a cluster of cells).
- Coverage limitation.

Ali et. al. (2010), also describes the possible reasons for poor handover success rate could be: congestion, bad antenna installation, the mobile station (MS) measures signal strength of another co-or- adjacent cell than presumed, and incorrect handover relations..

2.9.2.3 Connection Quality

Connection quality or service integrity is a measurement of how good the connection or how the data service is performing. It is subjected to constant changes in response to increasing coverage and capacity. The way to measure the quality will depend on the type of service and the availability of measurement in the network. In a telephone network, voice quality is an indicator of end-to-end speech transmission or connection quality. However, there is a clear limitation to provide user perspective of the quality from network measurements. Depending on the services, different performance indicators will be available, Popoola et. al. (2009); Gómez and Sánchez (2005).

Chapter Three

3 Data Mining and Knowledge Discovery

3.1 Basic Concepts

Complex and huge amount of data is generated and captured in every aspect of the industry such as marketing, insurance, finance, health, telecommunication, etc. However it is difficult for a human being to manually collect and process these data. This vast amount of data should be baked up on computerization technology to create a valuable and interesting knowledge, which brought data mining technology in to existence.

As indicated in Gorunescu (2011), the notion of data mining has emerged in many industries since 1990s as a process of "mining" data from the academic field for an intended purpose. Han, Kamber, and Pei (2011) discussed the term data mining as "the process of discovering interesting patterns and knowledge from large amounts of data. The data sources can include databases, data warehouses, the Web, other information repositories, or data that are streamed into the system dynamically" (P.18). There are also other terms synonyms to data mining such as knowledge mining from data, knowledge extraction, data or pattern analysis, data archaeology, and data dredging.

As discussed in Gorunescu (2011); Han et. al. (2011), data mining is a multidisciplinary field of information technology that adopts the techniques and terminologies from various disciplines such as Artificial Intelligence, Statistics, Database Systems, Data Warehouse, Information Retrieval, Machine Learning, Applications, Pattern Recognition, Visualization, Algorithms, and High Performance Computing.

Knowledge Discovery in Databases (KDD) is an automatic, exploratory analysis and modeling of large data repositories as well as the organized process of identifying crucial knowledge from large and complex data sets. Data Mining (DM) is the critical task in the KDD process involving the selection of algorithms that fits the data exploration task, development of model and discovery of previously unknown patterns. The model can be used to visualize the data generally

and to analyze, predict, group, associate, formulate rules… etc. specifically, Maimon and Rokach (2010).

The move towards offering wide range of contemporary services such as cellular phone, smart phone, Internet access, email, text messages, images, computer and web data transmissions, and other data traffic made the telecommunications industry to handle huge and complex data. This has made the application of data mining mandatory in the area for the accomplishment of many tasks such as detect fraudulent activities, efficient resource utilization, understand business dynamics, understand customers, and improve service quality which is in line with this study, Han et. al. (2011).

3.2 Data Mining Tasks

Functionalities of data mining specify the kinds of patterns found in data mining tasks that can be generally classified into two categories, descriptive and predictive. Although the boundaries between prediction and description are not sharp in such a way that some of the predictive models can be descriptive, to the degree that they are understandable, and vice versa, the distinction is useful to understand the overall discovery goal. The relative importance of prediction and description is specific to each data-mining application as the goals is achieved using a variety of particular data-mining methods, Fayyad, Piatetsky, Shapiro, and Smyth (1996b); Han et. al. (2011).

3.2.1 Predictive Methods

Predictive mining tasks perform induction on the current data in order to make prediction which is often referred to as supervised data mining. Moreover, prediction involves using some variables or fields in the database to predict the values of unknown or future values of other variables through the application of classification, regression, biases/anomalies detection… etc. Kumar, Tan, Steinbach (2001); Fayyad et. al. (1996b); Han et. al. (2011); Gorunescu (2011); Maimon and Rokach (2010). Basic prediction methods are described in the coming paragraphs as discussed by different scholars.

3.2.1.1 Classification

The natural process of classification where human mind organizes its knowledge differs from the classification in the context of data mining by the concept of taxonomy. The word ‘Taxonomy’ is

made up of two Greece words ‘tassein = classify’ and ‘nomos = science law’, appeared first as the science of classifying living organisms (alpha taxonomy). However, it is developed latter as the science of classification in general, including the principles of classification (taxonomic schemes) too. Thus, the taxonomic or classification is the process of categorizing a specific object (concept) based on the respective object (concept) properties, Gorunescu (2011).

Han et. al. (2011) defines classification as “a form of data analysis that extracts models describing important data classes. Such models called classifiers, predict categorical (discrete, unordered) class labels” (p.271). The book also discusses data classification as a two-step process that comprises model construction and model application to predict class labels for a given data. The first one is a learning step where the classification algorithm learns from the training set that contains a predetermined class label to build the classifier. The second one is a classification step where the model is applied to classify those data whose class label is unknown or previously unseen data different from the training set providing that the predictive accuracy of the model is acceptable. Classification has various applications such as fraud detection, target marketing, performance prediction, manufacturing, and medical diagnosis.

Gorunescu (2011) also describe the most widely used classification methods as follows:

- Decision/classification trees;
- Bayesian classifiers/Naive Bayes classifiers;
- Neural networks;
- Statistical analysis;
- Genetic algorithms;
- Rough sets;
- k-nearest neighbor classifier;
- Rule-based methods;
- Memory based reasoning;
- Support vector machines.

3.2.1.2 Regression

As indicated in Gorunescu (2011), statistically, regression analysis means the mathematical model which relates the values of a given variable (response/outcome/dependent variable) with

the values of other variables (predictor/independent variables). Regression analysis can be used to determine the quantitative relationship among multiple variables and to forecast the values of a variable on the basis of the values of other variables.

Kumar et al. (2001) clearly discussed the regression problem in relation with classification problem. Each record or instance or example in classification is represented by a tuple (x, y), where x is the set of explanatory variables associated with the object and y is the object's class label. The attributes x1, x2, ・ ・ ・ xk ∈ x can be discrete or continuous however the class label y must be a discrete variable its value is chosen from a finite set {y1, y2, ・ ・ ・ yc}. If y is a continuous variable, then this problem is known as regression.

In the context of data mining regression analysis has various applications such as in commerce to predict the dependent variable sales amounts of new product based on the independent variable advertising expenditure; in meteorology to predict the dependent variables wind velocities and directions as a function of temperature, humidity, air pressure, etc.; in stock exchange for time series prediction of stock market indices (trend estimation); in medicine to visualize the effect of parental birth weight/height on the dependent variable infant birth weight/height, Gorunescu (2011).

3.2.1.3 Time series Analysis

Time series data are records accumulated over time and they contains the large fraction of the world's supply of data For example, a company's sales, a customer's credit card transactions, and stock prices are all time series data. Such data can be viewed as objects with an attribute time. The objects are the snapshots of entities with values that change over time, Maimon and Rokach (2010); Sumathi and Sivanandam (2006).

According to Esling and Agon (2012), a time-series T is an ordered sequence of n real-valued variables which can be expressed as:

$$T = (t_1 . . . t_n) , t_i \in R.$$

And also a time series can be considered as the result of observation in a certain process where values are collected from the measurement at uniformly spaced time instants and according to a

given sampling rate. Thus, a time series is a set of contiguous time instants its series being univariate or multivariate.

Maimon and Rokach (2010) also indicate the major tasks of time series in data mining are: indexing, clustering, classification, prediction, summarization, anomaly detection, and segmentation.

3.2.1.4 Anomaly Detection

As described in Gorunescu (2011), terms like anomaly, extreme value, or outlier are somewhat equivalent and refer to a value which is found very far from the rest of data, and represent an isolated point of the dataset. In other words, they are infrequently observed data points which do not follow the distribution of the rest of the data.

Anomaly detection identifies data points that are different from the rest of the points in the data set. Thus, anomaly detection techniques can be applied to detect network intrusions and to predict fraudulent credit card transactions. Approaches to anomaly detection are based on statistics or based on distance or graph-theoretic notions, Kumar et. al. (2001).

3.2.2 Descriptive Methods

Descriptive mining tasks characterize properties of the data in a target data set. It focuses on finding human-interpretable patterns describing the underlying relationships in the data. Descriptive methods reveal patterns in data through the application of clustering, association rules, sequential patterns …etc. Moreover descriptive data mining includes the unsupervised and visualization aspects of data mining, Fayyad et. al. (1996b); Kumar et. al. (2001); Gorunescu (2011); Maimon and Rokach (2010).

3.2.2.1 Clustering

Unlike classification and prediction, which analyze class-labeled data objects, clustering analyzes data objects that do not have class label. The class labels are not present in the training data because they are not known so that clustering can be used to generate such labels. The objects are clustered or grouped with the aim of maximizing the intra class similarity and minimizing the interclass similarity. That is, objects within a cluster have high similarity in comparison to one another, but very dissimilar to objects in other clusters, Han and Kamber (2006). Thus, clustering can be defined as the process of grouping a collection of patterns into

distinct segments or clusters based on a suitable notion of closeness or similarity among these patterns.

According to Ye (2003), approaches to clustering are broadly classified in to two, these are:

Partitional methods partition the data set into k clusters, the problem being how to determine the "best" value for k. This can be done by guesswork, by application requirements, or by running the clustering algorithm several times with different values of k and selecting one of the solutions based on a suitable evaluation criterion. These algorithms were popular long before the emergence of data mining. The two most popular representatives are the k-means algorithm and the k-median algorithm.

Hierarchical methods can be of two types, agglomerative or bottom-up and divisive or top-down approaches.

The bottom-up approach starts with each object forming a separate group and successively merges these objects or groups which are closest according to some distance measure, until a termination condition is satisfied. The distance between two clusters can be measured as the distance between the closest pair, the farthest pair, or an average among all pairs and the result of these measures could be a single link, complete link, or average link. Single link is the most efficient however; it tends to give large clusters and is sensitive to noise. Complete link and average link methods yield more compact clusters even though they are computationally expensive.

The top-down approach starts with all the objects in the same cluster. Each successive iteration result in a cluster to split into smaller clusters according to some measure until a termination condition is satisfied. Divisive methods are less popular.

3.2.2.2 Association rules

Association rule mining results a set of dependence rules that predict the occurrence of a variable given the occurrences of other variables. For instance it can be used to identify products often purchased together; a task referred to as market basket analysis. As indicated in Han and Kamber (2006), rule interestingness is measured by rule support which reflects usefulness of the discovered rule and confidence which reflect certainty of the discovered rules.

In general, association rule mining can be regarded as a two-step process that involves finding all frequent item sets, and generating strong association rules from these frequent item sets.

Gorunescu (2011) discussed some popular algorithms in association rule discovery:

- **A priori algorithm**, proposed by Rakesh Agrawal and Ramakrishnan Srikant, being considered the best-known algorithm to mine association rules
- **FP-growth** (frequent pattern growth) algorithm, proposed by Jiawei Han, Jian Pei, Yiwen Yin, and Runying Mao
- **ECLAT** (Equivalence Class Clustering and Bottom-up Lattice Traversal), proposed by Mohammed Javeed Zaki, Srinivasan Parthasarathy, Mitsunori Ogihara, Wei Li

3.2.2.3 Sequential patterns

In sequential pattern mining, frequently occurring ordered events or subsequences are captured as patterns, the order of occurrence and the value of the events being important. According to Sumathi and Sivanandam (2006), sequential pattern mining can be applied to investigate changes in customer consumption or loyalty and suggest adjustments on the pricing and variety of goods in order to retain existing customers and attract new customers.

Moreover, Gorunescu (2011) discussed some real-life situations where sequential pattern techniques are employed:

- In supermarket, analysis of large database containing sequence of commercial transactions to streamlining the sale.
- In medicine, when diagnosing a disease, symptoms are record on each day and analyzed in real time to discover sequential patterns for that disease.
- In Meteorology, discovering patterns in global climate change such as global warming, discovering the possibility of occurrence of hurricanes, tsunamis, etc., based on previously captured events.

3.3 Challenges of Data Mining

Many scholars conduct different studies in order to identify the challenges in data mining. According to (Fayyad et al. 1996c), the data mining research community often challenged in developing methods that adopt data mining algorithms for real-world databases . One of the

characteristics of real-world databases is huge volume of data that results in several challenges such as:

- Computing complexity: Most algorithms have a computational complexity greater than linear, if they are applied on a database containing large number of attributes or tuples, there would be a significant execution time.
- Poor classification accuracy due to difficulties in finding the correct classifier as the search space increases.
- Storage problems: The main memory is not capable of storing the training dataset so that most machine learning algorithms use secondary storage.

Kumar et al. (2001) also indicates several important challenges in applying data mining techniques to large data sets:

Scalability: Scalable techniques are needed to handle the huge datasets created now days.

Dimensionality: Due to the "curse of dimensionality" in some application domains, the number of dimensions (or attributes of a record) of the data can be very large, which makes it difficult to analyze.

Complex Data: More complicated types of structured and semi-structured data have been generated and captured in recent years. The data analysis techniques should also be modified to handle the complex nature of such data.

Data Quality: Many data sets have problems with data quality, e.g., erroneous or inexact values, or missing values. Hence, there is a need for data mining techniques that can perform well even in such type of problematic situations or with reduced quality of data.

Yang and Wu (2006) also identify 10 challenging problems in data mining research that are sampled from a small segment of community. These are:

- Developing a unifying theory of data mining
- Scaling up for high dimensional data and high speed data streams
- Mining sequence data and time series data
- Mining complex knowledge from complex data

- Data mining in a network setting
- Distributed data mining and mining multi-agent data
- Data mining for biological and environmental problems
- Data Mining process-related problems
- Security, privacy and data integrity
- Dealing with non-static, unbalanced and cost-sensitive data

Each ranked important problem in data mining research is discussed in a great detail in the study for the interested reader.

3.4 Data Mining Process Models

As there are many types of data mining process models, there is no much difference among the various steps since most of them are interrelated. One could follow a model that fits the specific data mining project under study. In the article by Yang and Wu (2006), one of the 10 challenging problems to be solved in data mining research is Data Mining Process-Related Problems. Important topics exist in improving data-mining tools and processes through automation, as suggested by several researchers. Specific issues include how to automate the composition of data mining operations and building a methodology into data mining systems to help users avoid many data mining mistakes.

As described in Pressman (2005), a process model can be defined as a set of framework activities and tasks including inputs and outputs in every task to accomplish the desired job. As indicated in Tyrrell (2000), the following characteristics are crucial for a good process model:

- Effective, produce the right product.
- Maintainable, the problems should be identified quickly and easily in case of faults.
- Predictable, plans are used as the basis for allocating resources: both time and people.
- Repeatable, replicable irrespective of specific team and project.
- Quality, the product fitness for its purpose.
- Improvable, process needs further improvement.
- Traceable, easy follow up of the project status..

Mariscal, Marba, & Fernandez (2010) describe the evolution of fourteen data mining process models and methodologies. It is pointed out that KDD as the initial approach, and CRISP-DM as the central approach of the evolution diagram. Most of the approaches are based on these two process models. As shown in Figure 3.1, the process models are divided in to three: KDD related approaches, CRISP-DM related approaches, and other approaches. This paper will concentrate on the two main process models, KDD and CRISP-DM.

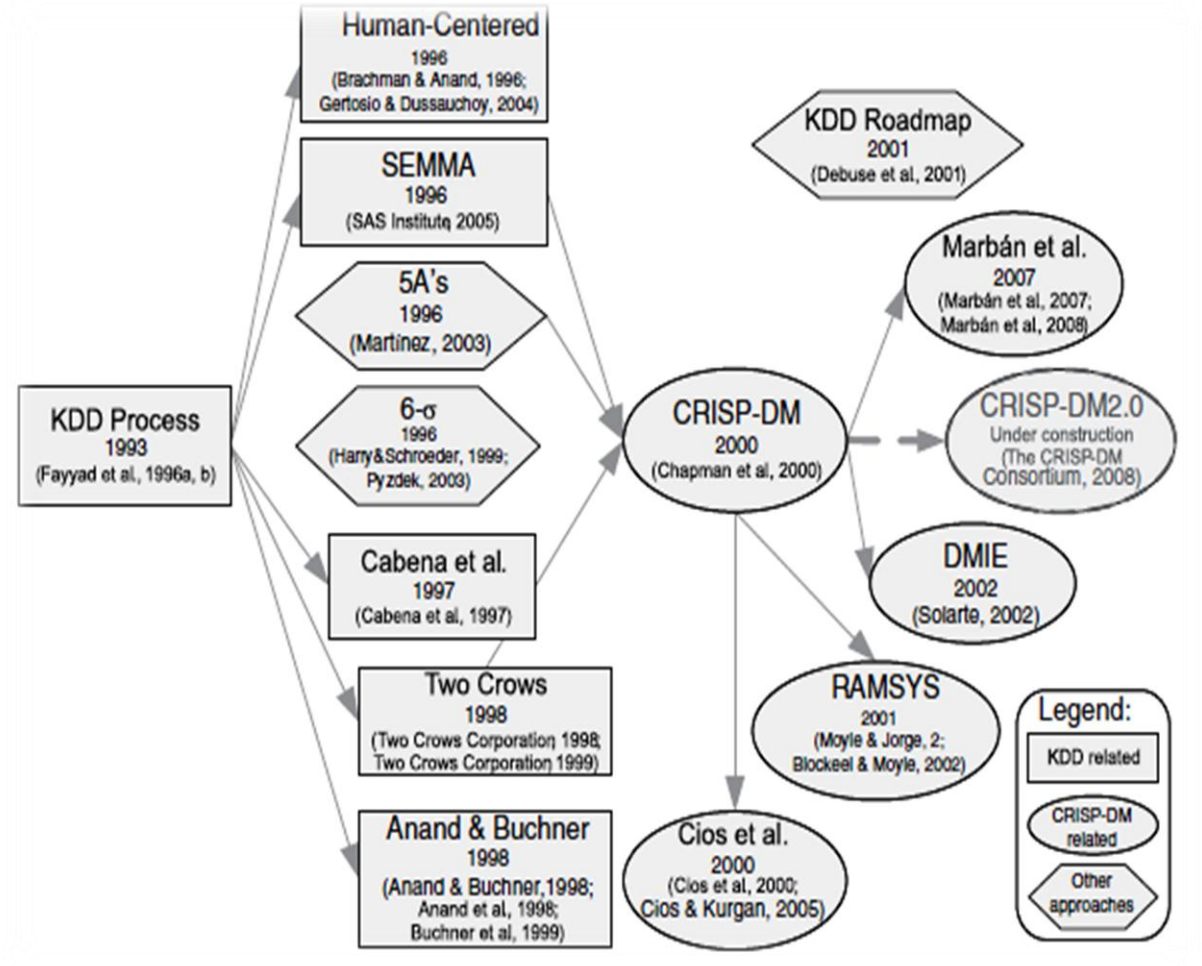


Figure 3.1 Evolution of data mining process models and methodologies (source: Mariscal et. al. (2010))

3.4.1 KDD Process

KDD is defined as the non-trivial process of identifying valid, novel, potentially useful and ultimately understandable patterns in data, Fayyad et al. (1996c). It refers to the overall process of discovering useful knowledge from data and involves the evaluation and interpretation of the patterns to make the decision of what qualifies as knowledge. It also includes the choice of encoding schemes, preprocessing, sampling and projections of the data before the data mining step. The data mining step refers to the application of algorithms for extracting patterns from data without the additional steps of the KDD process. Figure 3.2 presents the KDD process from the data point of view.

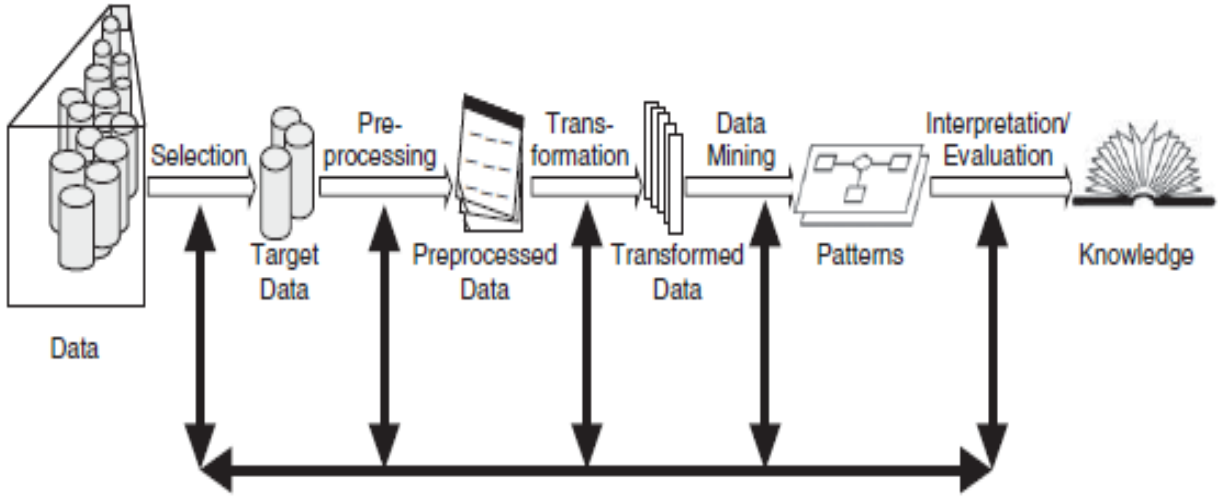


Figure 3.2 Overview of the steps constituting the KDD process (source: Fayyad et. al. (1996b))

According to Mariscal et. al. (2010), the KDD process is interactive and iterative that enables many decisions to be made by the user, involving nine steps, described from the practical point of view as follows:

Learning the application domain: It includes developing and understanding of the relevant prior knowledge and the goals of the application.

Creating a target data set: It includes selecting a data set or focusing on a subset of variables or data samples on which discovery is to be performed.

Data cleaning and preprocessing: It includes basic operations, such as removing noise or outliers, deciding on strategies for handling missing values, and deciding data base management system issues, such as data types, schema and mapping of missing and unknown values.

Data reduction and projection: It includes finding useful features that represent the data, depending on the goal of the task, and using dimensionality reduction or transformation methods to reduce the effective number of variables under consideration or to find invariant representations for the data.

Choosing the function of data mining: It includes deciding the purpose of the model derived by the data mining algorithm (e.g., summarization, classification, regression and clustering)

Choosing the data mining algorithm: It includes selecting method(s) to be used for searching patterns in the data, such as deciding which models and parameters may be appropriate and matching a particular data mining method with the overall criteria of the KDD process.

Data mining: It includes searching for patterns of interest in a particular representational form or a set of such representations, including classification rules or trees, regression, clustering, sequence modeling, dependency, association rules and line analysis.

Interpretation: It includes interpreting the discovered patterns and possibly returning to any of the previous steps, as well as possible visualization of the extracted patterns, removing redundant or irrelevant patterns and translating the useful ones into terms understandable by users.

Using discovered knowledge: It includes incorporating this knowledge into the performance system, taking actions based on the knowledge or simply documenting it and reporting it to interested parties, as well as checking for and resolving potential conflicts with previously believed (or extracted) knowledge.

3.4.2 CRISP-DM Process Model

As described in Chapman et al. (2000), CRISP (CRoss-Industry Standard Process for Data Mining) process mode involves six consecutive phases as shown in Figure 3.3. However, the sequence of the phases is not rigid since moving back and forth between different phases is always required. The output of each phase indicates the next phase or specific task to be performed in a phase. The arrows indicate the back and forth movement between the most

important and frequently dependent phases. As indicated by the outer circle, data mining is an iterative process in nature; it does not end once a solution is deployed. There are so many lessons to be learned during the process and from the deployed solution that can trigger new, often more-focused business questions. Moreover, the subsequent data mining processes will benefit from the experiences of previous ones. Each phase will be outlined as follows:

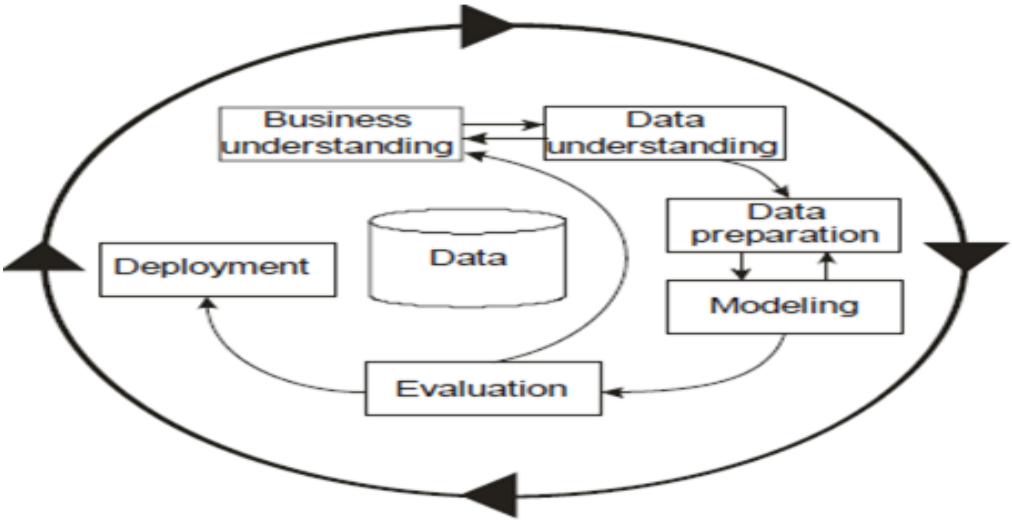


Figure 3.3 CRISP-DM process model (source: Chapman et al. (2000))

Business understanding: The business understanding phase focuses on understanding the project objectives and requirements from a business perspective, then converting this knowledge into a data mining problem definition and a preliminary plan designed to achieve the objectives.

Data understanding: The data understanding phase starts with initial data collection and proceeds with activities that enable you to become familiar with the data, identify data quality problems, discover first insights into the data, and/or detect interesting subsets to form hypotheses regarding hidden information.

Data preparation: The data preparation phase covers all activities needed to construct the final dataset from the initial raw data, which is the input data to the modeling tool. Data preparation tasks are likely to be performed multiple times and not in any prescribed order. These tasks include table, record, and attribute selection, as well as transformation and cleaning of data for modeling tools.

Modeling: In this phase, various modeling techniques are selected and applied, and their parameters are calibrated to optimal values. Typically, there are several techniques for the same data mining problem type. Some techniques have specific requirements on the form of data. Therefore, going back to the data preparation phase is often necessary.

Evaluation: At this stage in the project, you have built a model (or models) that appear to have high quality from a data analysis perspective. Before proceeding to final deployment of the model, it is important to thoroughly evaluate it and review the steps executed to create it, to be certain the model properly achieves the business objectives. A key objective is to determine if there is some important business issue that has not been sufficiently considered. At the end of this phase, a decision on the use of the data mining results should be reached.

Deployment: Creation of the model is generally not the end of the project. Even if the purpose of the model is to increase knowledge of the data, the knowledge gained will need to be organized and presented in a way that the customer can use it. It often involves applying "live" models within an organization's decision making processes

3.5 Application of Data Mining in Telecommunications

The telecommunications industry has been one of the earliest adopters of data mining technology and will continue to accelerate this adoption as companies strive to operate more efficiently and gain a competitive advantage in dealing with the huge amount of data generated in this area. According to Nadaf & Kadam (2013), these data include call detail data which describes the calls that traverse the telecommunications networks, network data which describes the state of the hardware and software components in the network, and customer data which describes the telecommunication customers. The amount of these data is so great that manual analysis of the data is difficult, if not impossible.

Telecommunications data have several interesting issues for data mining. The first is concerning scale since telecommunications databases contain billions of records and are amongst the largest in the world. The second issue is that the raw data is often not suitable for data mining. For example, both call detail and network data are time-series data that represent individual events. Before this data can be effectively mined, useful "summary" features must be identified and then the data must be summarized using these features. Because many data mining applications in the

telecommunications industry involve predicting very rare events, such as the failure of a network element or an instance of telephone fraud, rarity is another issue that must be dealt with. The fourth and final data mining issue concerns real-time performance; many data mining applications, such as fraud detection, require that any learned model/rules be applied in real-time, Nadaf & Kadam (2013); Joseph (2013).

3.5.1 Types of Telecommunication Data

Useful applications cannot be developed without understanding the various data used in telecommunications industries. So the early step in the data mining process is to understand the data. According to Joseph (2013), the different kinds of data used in this industry are mainly grouped into 3 different types: Call detail data, Network data, and Customer data.

Call detail data: This is the information about the call made by the subscriber, stored as the call detail record. As frequent calls are made by a large number of subscribers, the number of call detail records generated is huge. Since every call is placed on the network, the details are stored. Call detail record includes information like originating and terminating phone numbers, date, time and duration of call. Usually these call detail records are not directly used for Data Mining. A list of features can be generated from the call detail data such as:

- Average call duration
- Average number of call originated per day
- Average number of call received per day
- Percentage of no-answer calls
- Percentage of day time calls (office hours)
- Percentage of weekday calls (Monday – Friday)

These features can be used to generate a customer profile, which would be used to distinguish residential and business customers.

Network data: Telecommunications contain thousands of interconnected network components, that are capable of generating error and status messages which leads to a large volume of network data. These network data are used for network management functions like fault detection. As discussed in Weiss (2009), expert systems have been developed to analyze these

messages automatically, since the huge volume of network messages generated cannot be handled by technicians. However, these expert systems were expensive to develop as it is both time-consuming and difficult to encode the relevant knowledge from the human expert. Hence data mining technologies are used in identification of network faults by automatically extracting knowledge from network data. Network data is also generated in real time which can be accomplished by applying a time window to the data.

Customer data: Like any other business, telecommunication companies also have millions of customers. Hence it is very much essential to have a database for storing the information about these customers. Information about the customer will include:

- Name of the customer
- Address details
- Payment history
- Service plan and so on

3.5.2 Data Mining Tasks in Telecommunications

The telecommunications industry share many similarities with the retail industry in many data mining tasks such as constructing large-scale data warehouses, performing multi-dimensional visualization, OLAP, and in-depth analysis of trends, customer patterns, and sequential patterns. Both industries are benefited from data mining in many aspects like business improvements, cost reduction, customer retention, fraud analysis, and sharpening the edges of competition. Data mining tools that are customized to be applied for the telecommunications business are anticipated to provide solutions for the wide range of problems in this industry Han et. al. (2011).

In recent years, telecommunications have taken full advantage of access to data mining technology. There is a fierce competition in this area, especially among telecom operators, to improve the service quality and attract customers. In this regard, they should manage their customers and the market itself by finding a solution to the problems of identifying customer profile, to create and maintain their loyalty, and strategies for selling new products or services through the application of data mining. Among the problems that can be solved by data mining techniques in this area are: Fraud prediction in mobile telephony, Identifying loyal/profitable customer profile, Identifying factors influencing customer behavior concerning the type of phone

calls, Identifying risks regarding new investments in cutting-edge technologies (e.g., optic fiber, nano-technologies, semiconductors, etc.), Identifying differences in products and services between competitors are the vital once, Gorunescu F. (2011). Unlike the wide range of the issues, the advent of data mining technology promised solutions to these problems. Some of them are described in the following paragraphs.,

3.5.2.1 Fraud Detection

As indicated in Nadaf and Kadam (2013), fraud is a serious problem for telecommunications companies that results in a loss of revenue in billions of dollars each year. There are two types of fraud, namely subscription fraud and superimposition fraud. Subscription fraud occurs when a customer subscribes for a service with the intention of never paying for the usage charges. Superimposition fraud is committed by a legitimate subscription with some legitimate activity, but also includes some "superimposed" illegitimate activity by an individual other than the account holder. In the current telecom business activity, superimposition fraud is a bigger problem for the telecommunications industry.

3.5.2.2 Customer Segmentation and Profiling

Customer Segmentation is the process of dividing customers into the homogeneous groups according to their common attributes. These attributes include their likes, habits, actions. And Customer profiling means to describe the customers by their characteristics like age, gender, economic conditions, income, culture … etc. This Customer segmentation and profiling helps the telecommunications companies to decide which marketing actions should be taken for respective segment and allocating the resources, Weiss (2009).

3.5.2.3 Network Fault Isolation

Telecommunications networks are extremely complex configurations of hardware, software, and various network elements. Most of the network elements are capable of at least limited self-diagnosis, and these elements may collectively generate millions of status and alarm messages at each instance. In order to effectively manage the network, the status and alarm messages must be analyzed automatically in order to identify network faults in a timely manner—or before they occur and degrade network performance. A proactive response is essential to maintaining the reliability of the network. Because of the volume of the data, and because a single fault may

cause many different, seemingly unrelated, alarms to be generated, the task of network fault isolation is quite difficult. Data mining has a role to play in generating rules for identifying faults, Weiss (2009).

3.5.3 Local Researches in the Telecom Industry

As described in the previous paragraphs of section 3.5.2, the three main research areas of data mining in the context of telecommunications business are Fraud detection, Customer Segmentation and Profiling, and Network Fault Isolation. The local researches conducted on the application of data mining for the telecommunications industry can be summarized in two classes based on the three areas, one on the telecom fraud related to fraud detection and the other on customer relationship management (CRM) related to Customer Segmentation and Profiling.

Melaku (2009) have conducted a research on 'Applicability of Data Mining Techniques to Customer Relationship Management (CRM): The Case of Ethiopian Telecommunication Corporation's (ETC) Code Division Multiple Access (CDMA) Telephone Service.' On this research, CDMA call detail record (CDR) data along with billing information and the customers profile are collected. Different clustering and classification techniques of data mining are applied to cluster and classify high and low value customers.

Yeshinegus (2013) have conducted a research on 'Predictive Modeling for Fraud Detection in Telecommunications: The Case of ethio telecom.' On this study an effort has been made to predict fraudulent calls made using SIM boxes to terminate international calls. Sample Call Detail Record (CDR) data is used along with SMS, GPRS and on line charging service (OCS) data as a data set. Different classification methods such as J48, PART and multilayer perception algorithms are applied to predict fraudulent calls.

According to Weiss (2009), numerous data mining applications have been deployed in the telecommunications industry. However, most applications fall into one of the following three categories: marketing, fraud detection, and network fault isolation and prediction. It is clearly shown that the theme of this paper winds up on the last application.

3.6 Review of Related works

Different studies have been made on the QoS for mobile telecommunication by different scholars around the world. However, as to the reach of the knowledge of this researcher no local researches have been conducted on this area.

Pitas et. al. (2011) presents a paper entitled "QoS Mining Methods for Performance Estimation of Mobile Radio Networks" on the 10th International Conference on Measurement of Speech, Audio and Video Quality in Networks. This study present data mining methods for speech and video quality analysis and prediction. Accordingly, it is proved that quality of speech and video telephony services can be discovered applying algorithms like the k nearest-neighbor (KNN) classifier, decision trees and artificial neural networks. The study concludes that learning from QoS measurements is suitable for building evaluation and prediction models. Finally, it recommends conducting a study on the applicability of clustering algorithms.

Fong (2011), on his study entitled "Data Mining for Resource Planning and QoS Supports in GSM Networks", uses data mining to derive rules and extract traffic patterns that reveal critical information for setting values. The study tries to propose a new resource planning scheme that can dynamically adjusts the resource allocations according to the latest information of the traffic statues. As a result, resource management system is proposed for resource planning in order to facilitate dynamic resource allocation.

Lehtim aki (2008) studies on his doctoral research named "Data Analysis Methods for Cellular network Performance Optimization", the application of various data-analysis methods for the processing of the available measurement information in order to provide more efficient methods for performance optimization. On this research expert-based methods have been presented for the monitoring and analysis of multivariate cellular network performance data. These methods allow the analysis of performance bottlenecks having an effect in multiple performance indicators.

Multanen et. al. (2006) conduct a research entitled "Hierarchical analysis of GSM network performance data" to study a method for hierarchical examination and visualization of GSM data using the Self-Organizing Map (SOM) both in clustering and in visualization. As a result it is possible to reduce the amount of data and to give an extensive picture of the performance data.

Vehviläinen (2004) have conducted a doctoral research named 'Data Mining for Managing Intrinsic Quality of Service in Digital Mobile Telecommunications Networks'. In this study three data mining methods; rough sets, Classification And Regression Trees (CART), and Self-Organizing Map (SOM) were applied to the actual GSM network performance measurements preparing a data set of 3069 instances. The results show that the analyst can make good use of rough sets and Classification And Regression Trees (CART), because their information can be expressed in plain language rules that preserve the variable names of the original measurement. The study also recommends to concentrates on the preprocessing of the data set.

Chapter Four

4 Data Mining Methods for QoS Management

Different data mining algorithms are implemented to build a model using the data set collected for this specific study. Naïve Bays, Multilayer Perception, J48, and Simple k-means Algorithms are among the tested and evaluated classifiers and clusterers in this study. There are also other classifiers and clusterers implemented in different related researches as described in section 3.6, Review of Related works.

4.1 Decision Tree Classification

Decision tree induction is the learning of decision trees from class-labeled training tuples. A decision tree is a flowchart-like tree structure, where each internal node (non-leaf node) denotes a test on an attribute, each branch represents an outcome of the test, and each leaf node (or terminal node) holds a class label. The topmost node in a tree is the root node. Decision tree uses the traditional structure shown in Figure 4.1. It starts with a single root node that splits into multiple branches, leading to further nodes, each of which may further split or else terminate as a leaf node. Associated with each non-leaf node will be a test or question that determines which branch to follow. The leaf nodes contain the decisions, Maimon and Rokach (2010); Williams (2011); Han J. et. al., (2011).

Figure 4.1 Decision tree structure

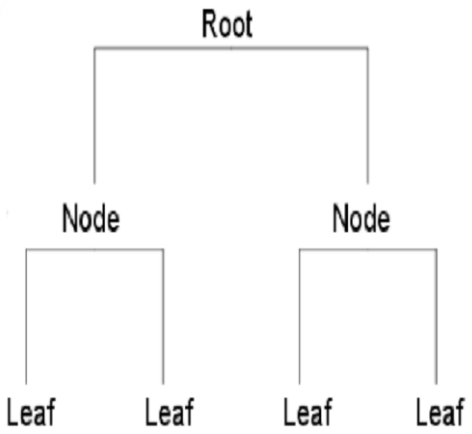
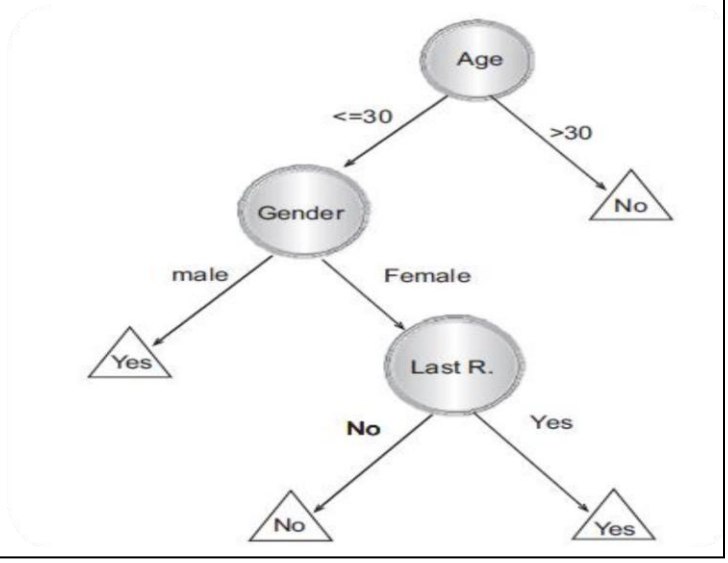


Figure 4.2 Decision Tree Presenting Response to Direct Mailing



Decision trees attempt to find a strong relationship between input values and target values in a group of observations that form a data set. When a set of input values is identified as having a strong relationship to a target value, then all of these values are grouped in a bin that becomes a branch on the decision tree. These groupings are determined by the observed form of the relationship between the bin values and the target, Ville (2006).

The construction of decision tree classifiers does not require any domain knowledge or parameter setting, and therefore is appropriate for exploratory knowledge discovery. Decision trees can handle multidimensional data. Their representation of acquired knowledge in tree form is intuitive and generally easy to assimilate by humans. The learning and classification steps of decision tree induction are simple and fast. Their attraction lies in the simplicity of the resulting model, where a decision tree (at least one that is not too large) is quite easy to view, understand, and, importantly explain. In general, decision tree classifiers have good accuracy. However decision trees do not always deliver the best performance, and represent a trade-off between performance and simplicity of explanation and successful use may depend on the data at hand, Williams (2011); Han J. et. al. (2011).

According to Gorunescu (2011), decision trees have three classical approaches:

i. Classification trees: when the prediction result is the class membership of data;

ii. Regression trees: when the predicted result is considered as a real number (e.g., oil price, value of a house, stock price, etc.);

iii. CART (or C&RT), i.e., Classification And Regression Tree: when both Classification and Regression trees are considered.

A. Tree Size

Generally, decision makers prefer less complex decision trees, since it is considered more comprehensive and easy to understand. According to Breiman et al. (1984), the tree complexity has a crucial effect on its accuracy. The tree complexity is explicitly controlled by the stopping criteria used and the pruning method employed. Usually the tree complexity is measured by one of the following metrics: the total number of nodes, total number of leaves, tree depth and number of attributes used.

B. Rule Induction in Trees

As described in Han J. et. al. (2011), there is a close relationship between decision tree induction and rule induction. Each path from the root of a decision tree to one of its leaves can be transformed into a rule simply by conjoining the tests along with the path to form the antecedent part, and taking the leaf's class prediction as the class value. For example, one of the paths in Figure 4.2 can be transformed into the rule: If customer age is less than or equal to 30, and the gender of the customer is "Male" – then the customer will respond to the mail. The resulting rule set can then be simplified to improve its comprehensibility to a human user, and possibly its accuracy.

C. Splitting Criteria

As indicated in Maimon and Rokach (2010), there are two types of splitting criteria in decision tree: Univariate Splitting Criteria and Multivariate Splitting Criteria.

Univariate Splitting Criteria: Univariate means that an internal node is split according to the value of a single attribute. Consequently the inducer searches for the best attribute upon which to split. The most common criteria in the literature includes: Impurity-based Criteria, Information Gain, Gini Index, Gain Ratio, etc.

Multivariate Splitting Criteria: In multivariate splitting criteria, several attributes may participate in a single node split test. Obviously, finding the best multivariate criteria is more complicated than finding the best univariate split. Furthermore, although this type of criteria may dramatically improve the tree's performance, these criteria are much less popular than the univariate criteria. Most of the multivariate splitting criteria is based on the linear combination of the input attributes.

D. Stopping Criteria

The growing phase continues until a stopping criterion is triggered. Conditions that are common for stopping rules are: All instances in the training set belong to a single value of *y*; The maximum tree depth has been reached; The number of cases in the terminal node is less than the minimum number of cases for parent nodes; If the node were split, the number of cases in one or more child nodes would be less than the minimum number of cases for child nodes; The best

splitting criterion is not greater than a certain threshold, Han J. et. al. (2011); Maimon and Rokach (2010).

E. Pruning

Employing tightly stopping criteria tends to create small and under–fitted decision trees. On the other hand, using loosely stopping criteria tends to generate large decision trees that are over–fitted to the training set. Pruning methods originally suggested in Breiman et al., (1984) were developed for solving this dilemma. According to this methodology, a loosely stopping criterion is used, letting the decision tree to over-fit the training set. Then the over-fitted tree is cut back into a smaller tree by removing sub–branches that are not contributing to the generalization accuracy. It has been shown in various studies that employing pruning methods can improve the generalization performance of a decision tree, especially in noisy domains.

When the goal is to produce a sufficiently accurate compact concept description, pruning is highly useful. Within this process, the initial decision tree is seen as a completely accurate one. Thus the accuracy of a pruned decision tree indicates how close it is to the initial tree, Maimon and Rokach (2010).

The dramatic growth of information system enable huge amount of data to be generated and collected day to day in many application areas so that there is a need for data mining algorithms such as decision tree to deal with this large datasets. I58, SLIQ, SPRINT, C4.5 (JAVA implementation is J48), CART and CHAID are among the decision tree algorithms that are described in many literatures. This study will concentrate on J48 decision tree algorithm which is the JAVA implementation of C4.5 algorithm, as it is used for experimentation.

4.1.1 J48 Decision Tree Algorithm

The best known decision tree learner is C4.5 by Quinlan (1993) and its java version, J48 the more recent upgrade by the same author, which is widely used and has been incorporated into commercial data mining tools as well as in the publicly available WEKA Data Mining toolbox. It is reliable, efficient and capable of dealing with large sets of training examples, Maimon and Rokach (2010).

It generates a classification-decision tree for the given data-set by recursive partitioning of data. The decision is grown using Depth-first strategy. The algorithm considers all the possible tests that can split the data set and selects a test that gives the best information gain. For each discrete attribute, one test with outcomes as many as the number of distinct values of the attribute is considered. For each continuous attribute, binary tests involving every distinct values of the attribute are considered. In order to gather the entropy gain of all these binary tests efficiently, the training data set belonging to the node in consideration is sorted for the values of the continuous attribute and the entropy gains of the binary cut based on each distinct values are calculated in one scan of the sorted data. This process is repeated for each continuous attributes, Zhao and Zhang (2007).

As described in Wu et al., (2007), given a set S of cases, C4.5 first grows an initial tree using the divide-and-conquer algorithm as follows:

- If all the cases in S belong to the same class or S is small, the tree is a leaf labeled with the most frequent class in S.
- Otherwise, choose a test based on a single attribute with two or more outcomes. Make the test the root of the tree with one branch for each outcome of the test, partition S into corresponding subsets S1, S2, . . . according to the outcome for each case, and apply the same procedure recursively to each subset.

There are usually many tests that could be chosen in this last step. C4.5 uses two heuristic criteria to rank possible tests: information gain, which minimizes the total entropy of the subsets {Si } (but is heavily biased towards tests with numerous outcomes), and the default gain ratio that divides information gain by the information provided by the test outcomes. Attributes can be either numeric or nominal and this determines the format of the test outcomes. For a numeric attribute A they are $\{A \leq h, A > h\}$ where the threshold h is found by sorting S on the values of A and choosing the split between successive values that maximize the criterion above. An attribute A with discrete values has by default one outcome for each value, but an option allows the values to be grouped into two or more subsets with one outcome for each subset. The initial tree is then pruned to avoid over-fitting, Wu et al., (2007).

4.2 Naïve Bayes Classification

Bayesian classifiers are statistical classifiers. They can predict class membership probabilities such as the probability that a given tuple belongs to a particular class. Bayesian classification is based on Bayes' theorem. Studies comparing classification algorithms have found a simple Bayesian classifier known as the naïve Bayesian classifier to be comparable in performance with decision tree and selected neural network classifiers. Bayesian classifiers have also exhibited high accuracy and speed when applied to large databases. The naive Bayes classifier assumes that attributes are independent, but it is still surprisingly powerful for many applications Zaki and Meira (2013); Han J. et. al. (2011).

As indicated in Harrington (2012), the advantage of Naïve Bayes classification is that it works with a small amount of data and handles multiple classes. However it is sensitive to how the input data is prepared. In general, Naïve Bayes works with nominal values.

4.2.1 Bays Theorem

According to Harrington (2012), Bayesian probability is named after Thomas Bayes, who was an eighteenth-century theologian. Bayesian probability allows prior knowledge and logic to be applied to uncertain statements.

As indicated in Zaki and Meira (2013), let the training dataset D consist of n points of x_i in a d-dimensional space, and let y_i denote the class for each point, with $y_i \in \{c_1, c_2 \ldots c_k\}$. The Bayes classifier directly uses the Bayes theorem to predict the class for a new test instance, x. It estimates the posterior probability $P(c_i|x)$ for each class c_i, and chooses the class that has the largest probability. The Bayes theorem allows inverting the posterior probability in terms of the likelihood and prior probability, which can be written as:

$$P(c_i|\mathbf{x}) = \frac{P(\mathbf{x}|c_i) \cdot P(c_i)}{P(\mathbf{x})}$$

Where $P(x|c_i)$ is the likelihood, defined as the probability of observing x assuming that the true class is c_i, $P(c_i)$ is the prior probability of class c_i, and P(x) is the probability of observing x from any of the k classes, given as

$$P(\mathbf{x}) = \sum_{j=1}^{k} P(\mathbf{x}|c_j) \cdot P(c_j)$$

Cios K., Pedrycz W., Swiniarski R., Kurgan L. (2007) stated Bayes' classification rule for multiclass objects with a multidimensional feature vector as:

"Given an object with a corresponding feature vector value x, assign an object to a class c_j with the highest a posteriori conditional probability P (c_j/x)."

In other words:

"For a given object with a given value **x** of a feature vector, assign an object to class c_j when P (c_j/**x**) > P (c_i/**x**), i = 1, 2…, l; i ≠ j"

The conditional probability p (c_i/x) is difficult to ascertain; however, using Bayes' theorem, we express it in terms of p (x/c_i), P (c_i) and P (x):

"A given object, with a given value x of a feature vector, can be classified as belonging to class c_j when

$$\frac{p(\mathbf{x}|c_j)P(c_j)}{p(\mathbf{x})} > \frac{p(\mathbf{x}|c_i)P(c_i)}{p(\mathbf{x})}, \quad i = 1, 2, \cdots, l; \; i \neq j"$$

After canceling the scaling probability p(x) from both sides, we obtain the following form of the Bayes classification rule:

"Assign an object with a given value x of a feature vector to class c_j when

p (**x**/cj) P (cj) > p (**x**/ci) P (ci) , i = 1, 2,…,l; i ≠ j"

In the sense of the minimization of the probability of classification, Bayes' error rule is the theoretically optimal classification rule. In other words, there is no other classification rule that yields lower values of the classification error.

4.3 Neural Network

Neural networks are computing models for information processing and are particularly useful for identifying the fundamental relationship among a set of variables or patterns in the data. They grew out of research in artificial intelligence; specifically, attempts to mimic the learning of the biological neural networks especially those in human brain which may contain more than 10^{11} highly interconnected neurons. They do share two very important characteristics with biological neural networks - parallel processing of information and learning, and generalizing from experience, Maimon and Rokach (2010).

The neural networks field was originally coined by psychologists and neurobiologists who sought to develop and test computational analogs of neurons. Roughly speaking, a neural network is a set of connected input/output units in which each connection has a weight associated with it. During the learning phase, the network learns by adjusting the weights so as to be able to predict the correct class label of the input tuples. Neural network learning is also referred to as connectionist learning due to the connections between units, Han J. et. al. (2011).

As described in Sorokosz & Zieniutycz (2012), the basic neural networks structure consists of two kinds of components: neurons - the processing elements and interconnections (synapses, links). Each link in the network is described by the weight parameter. Neurons can be classified into 3 groups: input, output and hidden neurons. Input neurons receive and process the signal from outside the networks, output neurons produce the out coming information (result) and neurons whose inputs and outputs are connected to other neurons are called hidden neurons.

Krose and Smagt (1996), describes the network topologies and the paradigm of learning in neural network as follows:

A. Network topologies

Feed-forward networks where the data flow from input to output units is strictly feed-forward. The data processing can extend over multiple (layers of) units, but no feedback connections are present, that is, connections extending from outputs of units to inputs of units in the same layer or previous layers.

Recurrent networks that do contain feedback connections; contrary to feed-forward networks, the dynamical properties of the network are important. In some cases, the activation values of the units undergo a relaxation process such that the network will evolve to a stable state in which these activations do not change anymore. In other applications, the change of the activation values of the output neurons is significant, such that the dynamical behavior constitutes the output of the network.

Classical examples of feed-forward networks include the Perceptron and Adaline; and that of recurrent networks are the Hopfield network, the Elman network (where some of the hidden unit activation values are fed back to an extra set of input units), and the Jordan network (where output values are fed back into hidden units).

B. Paradigms of learning

We can categories the learning situations in two distinct sorts. These are:

Supervised learning or Associative learning in which the network is trained by providing it with input and matching output patterns. These input-output pairs can be provided by an external teacher, or by the system which contains the network (self-supervised).

Unsupervised learning or Self-organization in which an output unit is trained to respond to clusters of pattern within the input. In this paradigm the system is supposed to discover statistically salient features of the input population. Unlike the supervised learning paradigm, there is no a priori set of categories into which the patterns are to be classified; rather the system must develop its own representation of the input stimuli.

4.3.1 Multilayer perception

Multilayer perceptions (MLPs) are the best known and most widely used kind of neural network. They are formed by units of the type shown in Figure 4.3. Each of these units forms a weighted sum of its inputs, to which a constant term is added. This sum is then passed through a nonlinearity, which is often called its activation function. Most often, units are interconnected in a feed-forward manner, that is, with interconnections that do not form any loops, as shown in Figure 4.4. For some kinds of applications, recurrent (i.e. non-feed-forward) networks in which some of the interconnections form loops are also used, Krose and Smagt (1996).

Figure 4.3 a unit of a multilayer Perceptron

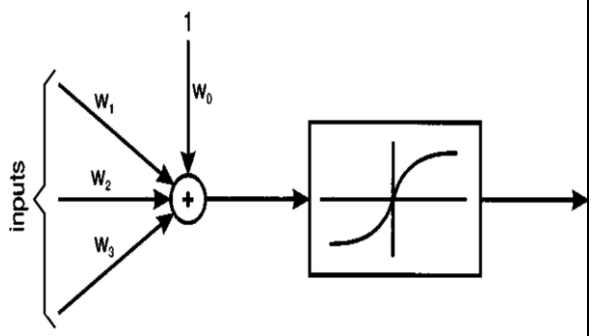
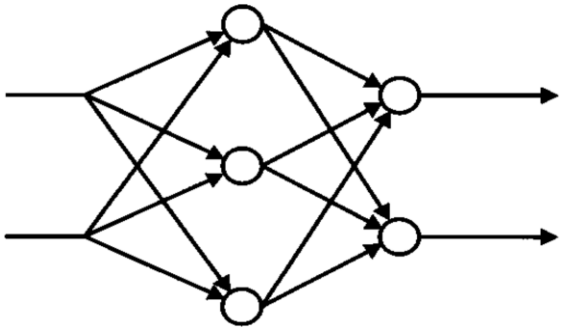


Figure 4.4 Example of a feed-forward network



MLP Structure

As described in Zhang and Gupta (2000), in the MLP structure, the neurons are grouped into layers. The first and last layers are called input and output layers respectively, because they represent inputs and outputs of the overall network. The remaining layers are called hidden layers. Typically, an MLP neural network consists of an input layer, one or more hidden layers, and an output layer, as shown in Figure 4.5.

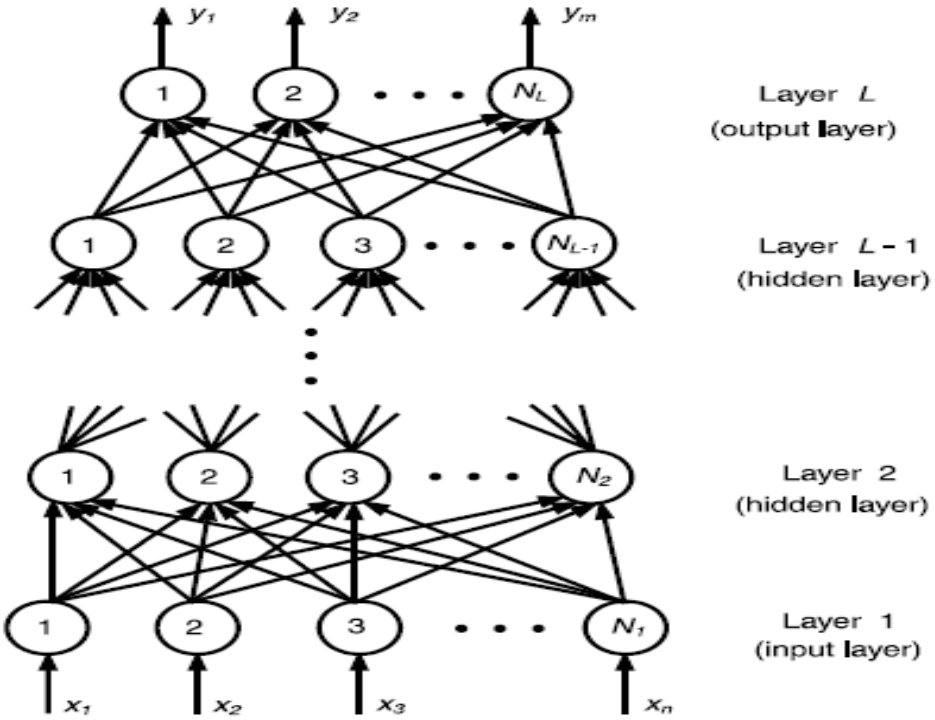


Figure 4.5 Multilayer Perception (MLP) Structure

Suppose the total number of layers is L. The 1st layer is the input layer, the L^{th} layer is the output layer, and layers 2 to L-1 are hidden layers. Let the number of neurons in l^{th} layer be N_l, l = 1, 2… L.

Let W^l_{ij} represent the weight of the link between j^{th} neuron of l-1th layer and i^{th} neuron of lth layer,, $1<=j<=N_{l-1}$, $1<=I<=N_l$. Let xi represent the i^{th} external input to the MLP, and z_i be the output of i^{th} neuron of l^{th} layer. We introduce an extra weight parameter for each neuron, wli0, representing the bias for i^{th} neuron of l^{th} layer. As such, w of MLP includes w^l_{ij}, j = 0, 1…N_{l-1}, i= l=2, 3… L, that is,

$$\boldsymbol{w} = [w^2_{10}\ w^2_{11}\ w^2_{12}\ \ldots,\ w^L_{N_L N_{L-1}}]^T$$

As briefly described in Han J. et. al. (2011); Maimon and Rokach (2010), the advantage of neural networks include: they involve long training times, high tolerance of noisy data as well as ability to classify patterns on which they have not been trained. They can be used when there is a little knowledge regarding the relationships between attributes and classes. They are well suited for continuous-valued inputs and outputs, unlike most decision tree algorithms. They have been successful on a wide array of real-world data, including handwritten character recognition, pathology and laboratory medicine, and training a computer to pronounce English text. Neural network algorithms are inherently parallel; parallelization techniques can be used to speed up the computation process. In addition, several techniques have been recently developed for rule extraction from trained neural networks. These factors contribute to the usefulness of neural networks for classification and numeric prediction in data mining. However neural networks have been criticized for their poor interpretability. For example, it is difficult for humans to interpret the symbolic meaning behind the learned weights and of "hidden units" in the network. These features initially made neural networks less desirable for data mining.

4.4 k-Means Clustering

As described in Harrington P. (2012), k-means is an algorithm that will find k clusters for a given dataset. The number of clusters k is user defined. Each cluster is described by a single point known as the centroid. Centroid means the single point is at the center of all the points in the cluster.

As indicated in Han J. et. al. (2011), this centroid can be defined by the mean or medoid of the objects (or points) assigned to the cluster. The difference between an object p ∈ Ci and ci, the representative of the cluster, is measured by dist (p, ci), where dist (x, y) is the Euclidean distance between two points x and y. The quality of cluster Ci can be measured by the within-cluster variation, which is the sum of squared error between all objects in Ci and the centroid ci, defined as:

$$\sum_{i=1}^{k} \sum_{p \in Ci} \text{Dist}(p, c_i)^2$$

Where E is the sum of the squared error for all objects in the data set; p is the point in space representing a given object; and c_i is the centroid of cluster C_i (both p and c_i are multidimensional). In other words, for each object in each cluster, the distance from the object to its cluster center is squared, and the distances are summed. This objective function tries to make the resulting k clusters as compact and as separate as possible.

4.4.1 k-Means Algorithm

Gorunescu (2011) describes the general scheme of the k-means algorithm as follows:

1) Select k points at random as cluster centers.
2) Assign instances to their closest cluster center according to some similarity distance function.
3) Calculate the centroid or mean of all instances in each cluster (this is the 'mean' part of the algorithm).
4) Cluster the data into k groups where k is predefined.
5) GOTO the step 3. Continue until the same points are assigned to each cluster in consecutive rounds.

The time complexity of the k-means algorithm is $O(n*k*t)$, where n is the total number of objects, k is the number of clusters, and t is the number of iterations. Normally, $k \ll n$ and $t \ll n$, therefore, the method is relatively scalable and efficient in processing large data sets, Han J. et. al. (2011).

According to Maimon and Rokach (2010), the k-means algorithm has an advantage when it is compared to other clustering methods (e.g. hierarchical clustering methods) on that it has non-linear complexity, ease of interpretation, simplicity of implementation, speed of convergence and adaptability to sparse data. However the *k-means* algorithm works well only on data sets having isotropic clusters, and is not as versatile as single link algorithms. Moreover, this algorithm is sensitive to noisy data and outliers (a single outlier can increase the squared error dramatically); it is applicable only when mean is defined (namely, for numeric attributes); and it requires the number of clusters in advance, which is not trivial when no prior knowledge is available. The use of the *k-means* algorithm is often limited to numeric attributes.

Han J. et. al. (2011) points out approaches to make the k-means method more efficient on large data sets. One is to use a good-sized set of samples in clustering. Another is to employ a filtering approach that uses a spatial hierarchical data index to save costs when computing means. A third approach explores the micro-clustering idea, which first groups nearby objects into "micro-clusters" and then performs k-means clustering on the micro-clusters.

Chapter Five

5 Experimentation and Analysis

As indicated from the outset, the objective of this research is to analyze the performance of the GSM network based on the data extracted from the ethio telecom live mobile network using data mining techniques. Thus, the experimentation is conducted on the basis of the selected process model which is Knowledge Data Discovery (KDD) indicated in Section 1.6. Different data mining algorithms such as J48 Decision Tree, Naïve Bayes, Multilayer Perception, and k-means are applied in this experimentation. On the top of all these, Knowledge from domain experts is crucial to understand the application domain where this study is conducted.

5.1 Experiment Design

The computer used for this experimentation is Dell-E5430, Intel (R), Core I7, CPU 3.oo GHz, RAM 4.00 GHz, and 32 bit operating system. Different software tools are involved in this experiment including Microsoft Excel to filter out and format the desired data before it is changed into Attribute Relation File Format (ARFF) data format. The open source data mining tool selected for this study is Weka since it is platform independent as it is written in java and also based on the researcher's familiarity with the tool. The Weka version used for this specific experimentation is Weka 3.7.11.

5.2 KDD Processes

As described in section 3.4.1, the KDD process model described from the practical viewpoint proposed by Fayyad et al. (1996b) can be performed with in nine steps: Learning the application domain, creating a target data set, data cleaning and preprocessing, data reduction and projection, choosing the function of data mining, choosing the data mining algorithm, data mining, interpretation, and using the discovered knowledge.

5.2.1 Learning the application domain

In order to acquire the domain knowledge on the application area of telecommunication network environment relevant books, researches, and manuals are referred as well as practical knowledge

of domain experts such as telecommunication engineers in the actual network optimization task has been acquired through unstructured interview. Moreover, the researcher's previous experience is also helpful to align the goal of the study with the application area.

5.2.2 Creating target data set

As indicated from the outset, the target data set used for this study will be extracted from the network management system database of the live telecommunication mobile network for the cells covered under the scope. Three kinds of data sets are extracted based on the time period where the KPI measurements are taken. The first indicates a one day or 24 Hour KPI measurement per one hour query granularity where the query time is 2013-12-30 00:00:00 - 2013-12-31 00:00:00, the second indicates the day high traffic hour (10:00 to 11:00) and the night high traffic hour (20:00 to 21:00) per one hour query granularity where the query time is 2013-12-23 00:00:00 - 2013-12-30 00:00:00 and the effective time is 10:00:00-11:00:00 20:00:00-21:00:00 , and the third indicates a one month KPI measurement per one day query granularity where the Query time is 2013-11-01 00:00:00 - 2013-12-01 00:00:00. The initial data set contains more than 270 attributes and 33,331 rows for the first, 19,420 rows for the second and 40,741 rows for the third data set.

The reason that the data sets are extracted in three kinds is for simplicity of analysis. The one day KPI dataset enable to observe the cumulative effects of the KPI values in 24 hour, the day and night high traffic hour KPI dataset enable to observe the effects of the KPIs during high traffic hour, and the one month KPI dataset enables to observe the consistency and the cumulative effects of the KPI values within one month.

5.2.3 Data cleaning and preprocessing

As indicated in the previous section the dataset extracted for this study contains more than 270 attributes (KPIs) however nineteen of these attributes are not informative for this specific study and removed in order to clean the data. These attributes include: Index, Start Time, End Time, Query Granularity, SUBNETWORK, SUBNETWORK Name, ME Name, ME, SITE, BTS, SITE Name, BTS NAME, Location(LAC), CI(CI), cell latitude, cell longitude, cell anteHeight, cell anteAzimuth, cell address.

As described in Witten, Frank, and Hall (2011), errors that appear during measurement of numeric values might cause outliers. Erroneous values often create a significant deviation from the pattern that might be extracted in the remaining values. Thus, such inaccurate values should be treated though it is difficult to find, particularly without specialist domain knowledge. Such kinds of problems are visualized in the extracted data set of two specific KPIs, Standalone Dedicated Control Channel (SDCCH) in service rate and Traffic Channel (TCH) in service rate, whose value is below 50%. These KPIs generally indicate the health of the TRX in the corresponding cell, which might directly or indirectly affected by a certain alarm event (minor, major, or critical) generated in the interconnected network element. In this regard, it is mandatory to refer the recommendation of experts in the mobile network optimization and to examine the data set at hand.

When the data set is examined for these two KPIs, SDCCH in service rate and TCH in service rate of values less than or equal to 50%, it is possible to generalize that the corresponding values of other KPIs are subjected to inaccurate value. Even in the case of both SDCCH in service rate and TCH in service rate equals 0% (when the cell is totally down), out of ten KPIs eight of them have a KPI value even better than the standard for most of the instances. This can be taken as manifestation of inaccuracy. As shown in Table 5.1 only Call Success Rate (CSR) and Call Setup Success Rate (CSSR) KPIs respond to the very decrease of both SDCCH and TCH in service rate, the rest KPIs (SDCCH-CR, TCH-CR, DCR, SDCCH-CD, TCH-CDR, HOSR, HOSR-I, and HOSR-O) indicate a KPI value even better than the standard indicated in the heading columns.

SDCCH in service rate (%)	TCH in service rate (%)	CSR (%) (>=96 %)	SDCCH-CR (%) (<=0.5 %)	TCH CR (%) (<=2%)	DCR (%) (<=2 %)	SDCCH-CD (%) (<=0.5 %)	TCH CDR (%) (<=2 %)	HOSR (%) (>=96 %)	CSSR (%) (>=96 %)	HOSR-I (%) (>=96%)	HOSR-O (%) (>=96 %)
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00	0.00	100.00	100.00
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00	0.00	100.00	100.00
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00	0.00	100.00	100.00
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00	0.00	100.00	100.00
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00	0.00	100.00	100.00
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00	0.00	100.00	100.00
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00	0.00	100.00	100.00
0.00	0.00	0.00	0.00	100.00	0.00	0.00	0.00	100.00	0.00	100.00	100.00
0.00	0.00	0.00	0.00	100.00	0.00	0.00	0.00	100.00	0.00	100.00	100.00
33.33	30.16	27.33	45.82	70.10	0.87	0.05	0.72	94.33	27.57	96.88	88.89

Table 5.1 Sample KPI values for SDCCH and TCH in service rates less than 50%

However, this problem is improved when both SDCCH and TCH in service rate KPI values are progressed. Thus, domain experts recommend considering the corresponding KPI values that have more than 50% SDCCH and TCH in service rate. As indicated in Table 5.2, when SDCCH and TCH in service rate KPIs are increased above 50%, from where the cell is partially working, the corresponding KPI values are very close to a real value. Thus, the study will also include such data in the final data set.

SDCCH in service rate (%)	TCH in service rate (%)	CSR (%) (>=96 %)	SDCCH-CR (%) (<=0.5 %)	TCH CR (%) (<=2 %)	DCR (%) (<=2 %)	SDCCH-CDR (%) (<=0.5 %)	TCH CDR (%) (<=2 %)	HOSR (%) (>=96 %)	CSSR (%) (>=96 %)	HOSR-I (%) (>=96 %)	HOSR-O (%) (>=96 %)
70.00	64.63	98.04	0.00	0.00	0.00	0.00	0.00	100.00	98.04	100.00	100.00
75.00	72.55	100.00	0.00	0.00	0.00	0.00	0.00	100.00	100.00	100.00	100.00
64.29	60.65	97.04	0.00	0.00	0.76	0.00	0.20	98.13	97.78	97.69	98.54
71.43	69.40	99.40	0.00	0.00	0.14	0.04	0.07	98.08	99.54	97.68	98.44
75.00	84.80	99.59	0.00	0.00	0.41	0.00	0.20	97.58	100.00	97.09	98.16
66.67	76.47	99.61	0.00	0.00	0.00	0.05	0.00	99.42	99.61	100.00	99.32
66.67	78.78	99.37	0.00	0.00	0.28	0.07	0.24	99.32	99.65	99.65	99.16
80.00	91.86	100.00	0.00	0.00	0.00	0.00	0.00	100.00	100.00	100.00	100.00
85.71	91.76	100.00	0.00	0.00	0.00	0.00	0.00	100.00	100.00	100.00	100.00
66.67	74.07	100.00	0.00	0.00	0.00	0.00	0.00	95.65	100.00	100.00	91.36

Table 5.2 Sample KPI values for SDCCH and TCH in service rates greater than 50%

5.2.4 Data reduction

In the context of data reduction, the strategies employed in this phase involve considering those KPIs that are categorized by the company to assess the general quality of the network among the large amount of attributes in the data set and leave the rest bunch of KPIs. Thus, only ten KPIs will be covered in this study as shown in Table 5.3.

S. No	Attribute (KPI)	Description	Data Type
1	Call Success Rate (CSR)	Rate of calls going until normal release.	Numeric
2	SDCCH Congestion Rate (SDCCH-CR)	Rate of SDCCH not allocated during radio link establishment procedure due to congestion on the Air interface	Numeric
3	TCH Congestion Rate (TCH-CR)	Rate of blocked calls due to resource unavailability	Numeric
4	Drop Call Rate (DCR)	Rate of calls not completed successfully.	Numeric
5	Handover success rate (HOSR)	Rate of successful handovers (intracell + intercell).	Numeric
6	Call setup success rate (CSSR)	Rate of call attempts until TCH successful assignment.	Numeric
7	SDCCH call drop rate (SDCCH-CDR)	Indicates that how good the cell/system is at preserving calls	Numeric
8	TCH call drop rate	Rate of TCHs dropped over the total amount of calls established in the cell	Numeric
9	Handover in success rate	Rate of successful incoming (intracell + intercell) SDCCH and TCH handovers.	Numeric
10	Handover out success rate	Rate of successful outgoing (intracell + intercell) SDCCH and TCH handovers	Numeric

Table 5.3 Attributes (KPIs) selected for the study

The other important point is KPIs threshold point, beyond which network quality degradation is confirmed. KPI threshold points are different from operator to operator and from vendor to vendor, there is no internationally agreed threshold point for each KPI. For the purpose of this study the threshold points used in the company are considered which is shown in Table 5.4.

CSR	SDCCH CR	TCH CR	DCR	SDCCH CDR	TCH CDR	HOSR	CSSR	HOSR-I	HOSR-O
>=96%	<=0.5%	<=2%	<=2%	<=0.5%	<=2%	>=96%	>=96%	>=96%	>=96%

Table 5.4 Threshold point for selected attributes (KPIs)

Having all the above prior knowledge in mind, it would be easy to prepare the given data set for the next data mining tasks after it is processed through the following important step which is discretization.

Discretization: As indicated in Han et. al. (2011), Data discretization reduces numeric data by mapping values in to intervals. Such methods can be used to map these intervals with concept hierarchies for the data. Discretization techniques involve binning, histogram analysis, cluster analysis, decision tree analysis, and correlation analysis. Whatever is the case, data discretization is determination of split-points or data values for partitioning an attribute range provided that the split points should represent the distribution of the data. To this end, different discretization techniques are tested and compared with the distribution of the data. Finally, after discussing with the domain experts, the discretization technique that best represents the data is to find a single split point (**s**) between the threshold point (**t**) and the ideal value (the maximum desirable value) (**i**) based on histogram analysis and visual inspection of the actual data distribution of each KPI. Moreover, the other point (beyond t) represents those KPIs that are below the threshold point and grouped under the same category as all of them do not fulfill the recommended standard. As a result the data can be discretized in to three categories that are mapped with the concept hierarchy as shown in the following Table. KPI values are between 0 and 1 and this values are described in percent in the actual measurement data, for example 0 is equivalent to 0%, 1 is equivalent to 100%, t is equivalent to (t*100)%.

KPI Category	Description	Histogram Representation
0	represents all KPI values that are under the threshold point	(0,t) or (t,1)
1	represents all KPI values that are grouped as normal KPI value	[t, s) or (s, t]
2	represents all KPI values that exceeds the normal KPI values	[s,1] or [0,s]

Table 5.5 Concept hierarchy of discretized attributes (KPIs)

In order to map the above representation with each KPI data, a splitting point should be indicated between the threshold point and the ideal value (the maximum desirable value) of that specific KPI based on visual inspection and recommendations of domain experts. The data distribution is visualized using Weka built in function for each KPI, for the one day or 24 hour KPI data set as shown below.

1. **Call Success Rate (CSR):** The threshold for CSR is 96%; all values below this point are categorized as '0' or manifestation of a degraded service. There are 23,765 instances that are within the threshold point under this KPI.

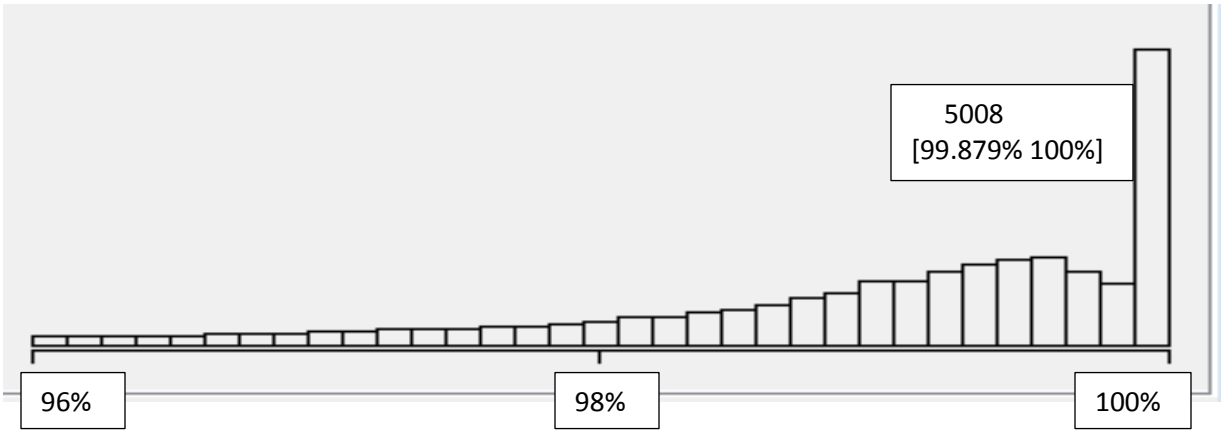


Figure 5.1 Distribution of the CSR KPI data

As shown from the above CSR KPI data distribution, starting from the threshold point (96%) the distribution increases slightly up to 99.879%, after this point the distribution indicates a considerable increase. Based on these concepts, discretization of the CSR KPI data can be summarized by the following table.

0	1	2
CSR KPI < 96%	96% <= CSR KPI < 99.879	CSR KPI >= 99.879

Table 5.6 Discretization of CSR KPI (t= 0.96 or 96% and s = 0.99879 or 99.879)

2. **Standalone Dedicated Control Channel-Congestion Rate (SDCCH-CR)**: The threshold for SDCCH-CR is 0.5%, all values above this point are categorized as '0' or manifestation of a degraded service. There are 26,499 instances that are within the threshold point under this KPI.

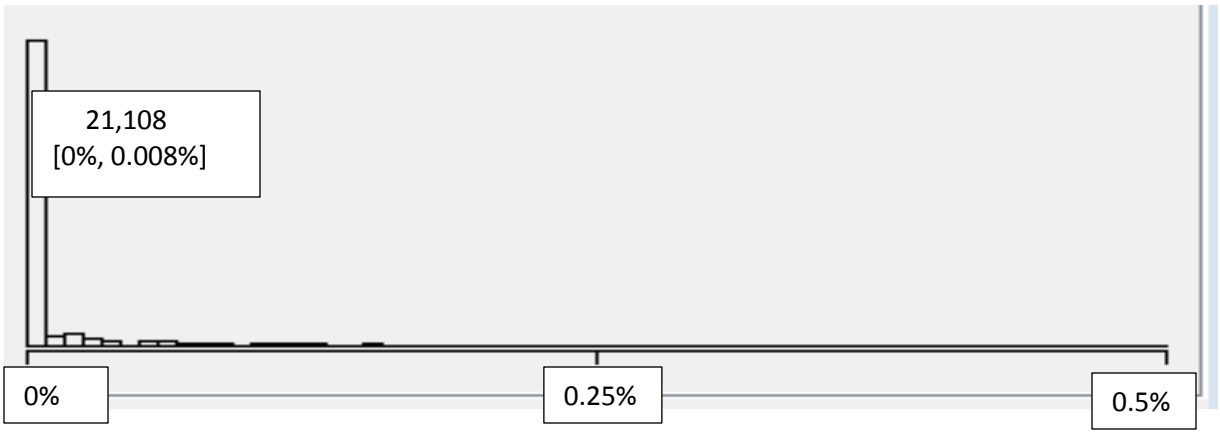


Figure 5.2 Distribution of the SDCCH-CR KPI data

As shown from the above SDCCH-CR KPI data distribution, starting from the threshold point (0.5%) the distribution increases slightly up to 0.008%, after this point the distribution indicates a considerable progress. Based on these concepts, discretization of the SDCCH-CR KPI data can be summarized by the following table.

0	1	2
SDCCH-CR KPI > 0.5%	0.008% < SDCCH-CR KPI <= 0.5%	SDCCH-CR KPI <= 0.008%

Table 5.7 Discretization of SDCCH-CR KPI (t = 0.5 or 0.005% and s = 0.8 or 0.008%)

3. **Traffic Channel-Congestion Rate (TCH-CR):** The threshold for TCH-CR is 2%; all values above this point are categorized as '0' or manifestation of a degraded service. There are 27,670 instances that are within the threshold point under this attribute. The distribution of this KPI is shown in the following figure.

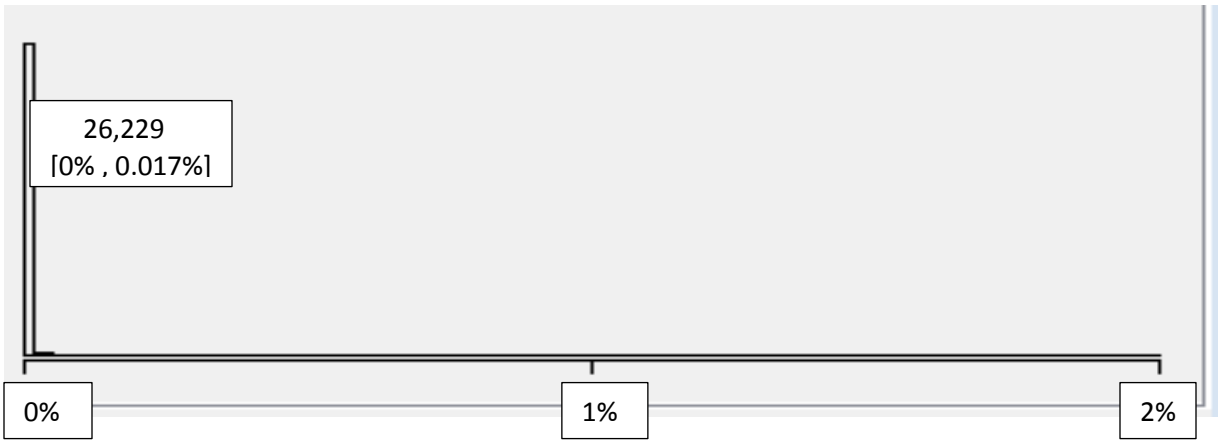


Figure 5.3 Distribution of the TCH-CR KPI data

As shown from the above TCH-CR KPI data distribution, starting from the threshold point (2%), the distribution seems to be constant and not considerable up to 0.017%, after this point the distribution indicates a considerable increase. Based on these concepts, discretization of the TCH-CR KPI data can be summarized by the following table.

0	1	2
TCH-CR KPI > 2%	0.017% < TCH-CR KPI <= 2%	TCH-CR KPI <= 0.017%

Table 5.8 Discretization of TCH-CR KPI (t = 0.02 or 2% and s = 0.00017 or 0.017%)

4. **Dropped Call Rate (DCR):** The threshold for DCR is 2%; all values above this point are categorized as '0' or manifestation of a degraded service. There are 26,275 instances that are within the threshold point under this KPI.

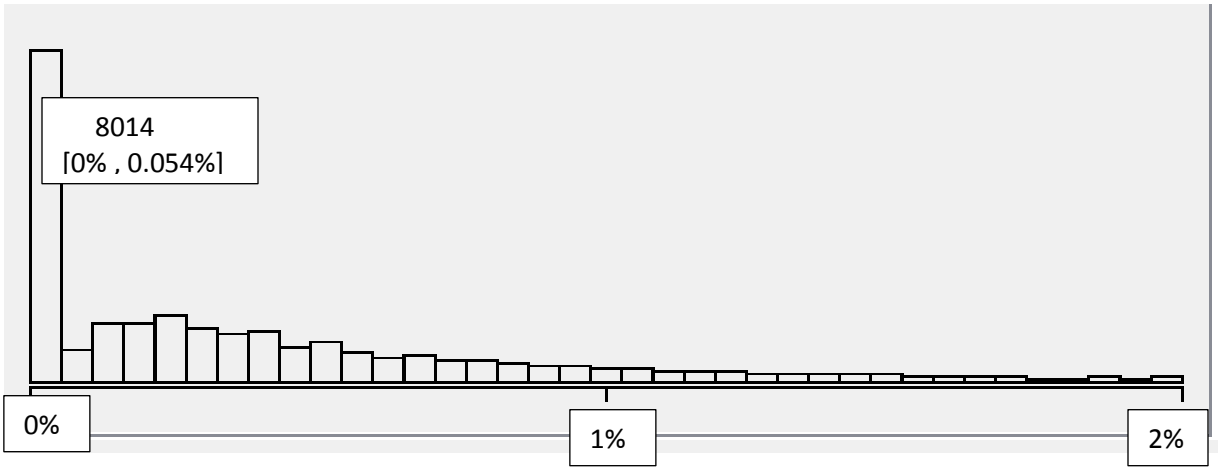


Figure 5.4 Distribution of the DCR KPI data

As shown from the DCR KPI data distribution, starting from the threshold point (2%) the distribution increases slightly up to 0.054%, after this point the distribution indicates a considerable increase. Based on these concepts, discretization of the SDCCH-CR KPI data can be summarized by the following table.

0	1	2
DCR KPI > 2%	0.054% < DCR KPI <= 2%	DCR KPI <= 0.054%

Table 5.9 Discretization of DCR KPI (t = 0.02 or 2% and s =0.00054 or 0.054%)

5. **SDCCH in Call Drop Rate (SDCCH-CDR):** The threshold for SDCCH-CDR is 0.5%; all values above this point are categorized as '0' or manifestation of a degraded service. There are 28,384 instances that are within the threshold point under this KPI.

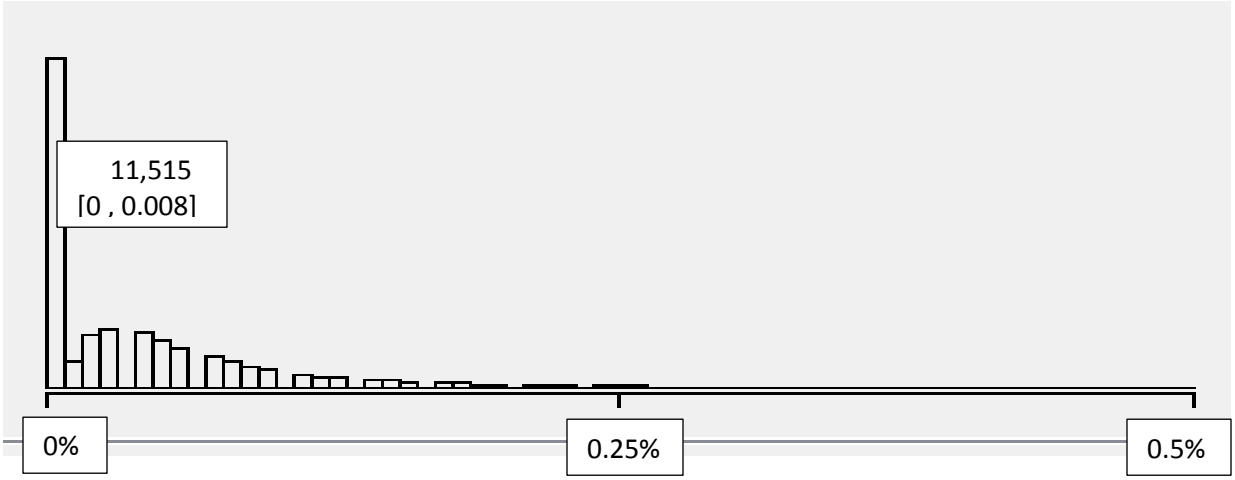


Figure 5.5 Distribution of the SDCCH-CDR KPI data

As shown from the above SDCCH-CDR KPI data distribution, starting from the threshold point (0.5%) the distribution increases slightly up to 0.008%, after this point the distribution indicates a considerable increase. Based on these concepts, discretization of the SDCCH-CDR KPI data can be summarized by the following table.

0	1	2
SDCCH-CDR KPI > 0.5%	0.008% < SDCCH-CDR KPI <= 0.5%	SDCCH-CDR KPI <= 0.008%

Table 5.10 Discretization of SDCCH-CDR KPI (t = 0.05 or 2% and s = 0.00008 or 0.008%)

6. **TCH in Call Drop Rate (TCH-CDR):** The threshold for TCH-CDR KPI is 2%; all values above this point are categorized as '0' or manifestation of a degraded service. There are 27,446 instances that are within the threshold point under this KPI.

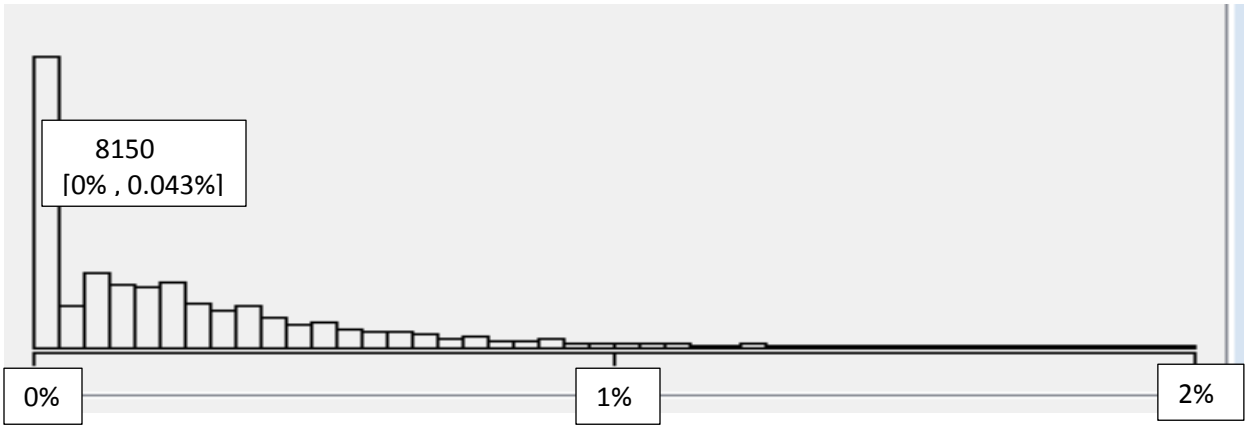


Figure 5.6 Distribution of the TCH-CDR KPI data

As shown from the above TCH-CDR KPI data distribution, starting from the threshold point (2%), the distribution increases slightly up to 0.043%, after this point the distribution indicates a considerable increase. Based on these concepts, discretization of the TCH-CDR KPI data can be summarized by the following table.

0	1	2
TCH-CDR KPI > 2%	0.043% < TCH-CDR KPI <= 2%	TCH-CDR KPI <= 0.043%

Table 5.11 Discretization of TCH-CDR KPI (t = 0.02 or 2% and s = 0.00043 or 0.043%)

7. **Handover Success Rate (HOSR):** The threshold for CSR is 96%; all values below this point are categorized as '0' or manifestation of a degraded service. There are 22,893 instances that are within the threshold point under this KPI.

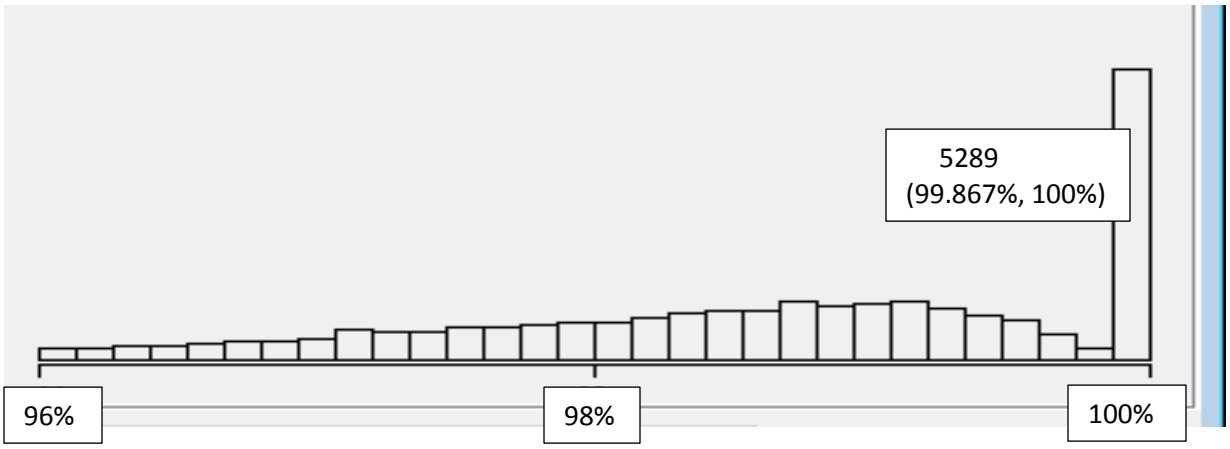


Figure 5.7 Distribution of the HOSR KPI data

As shown from the above HOSR KPI data distribution, starting from the threshold point (96%), the distribution increases slightly up to 99.867%, after this point the distribution indicates a considerable increase. Based on these concepts, discretization of the HOSR KPI data can be summarized by the following table.

0	1	2
CSR KPI < 96%	96% <= CSR KPI < 99.867	CSR KPI >= 99.867

Table 5.12 Discretization of HOSR KPI (t= 0.96 or 96% and s = 0.99867 or 99.867)

8. **Call Setup Success Rate (CSSR):** The threshold for CSR is 96%; all values below this point are categorized as '0' or manifestation of a degraded service. There are 25,190 instances that are within the threshold point under this KPI.

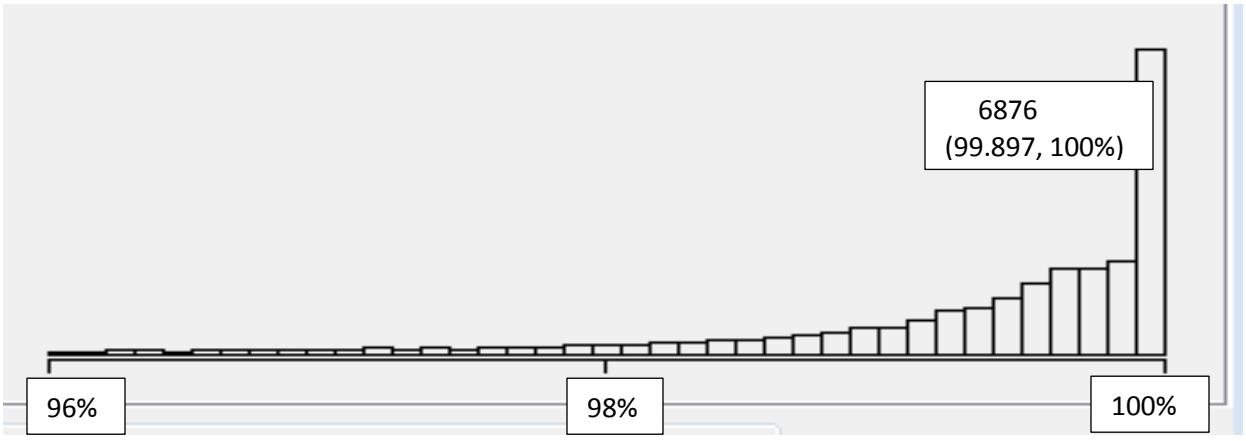


Figure 5.8 Distribution of the CSSR KPI data

As shown from the above CSSR KPI data distribution, starting from the threshold point (96%), the distribution increases slightly up to 99.897%, after this point the distribution indicates a considerable increase. Based on these concepts, discretization of the CSSR KPI data can be summarized by the following table.

0	1	2
CSSR KPI < 96%	96% <= CSSR KPI < 99.897	CSSR KPI >= 99.897

Table 5.13 Discretization of CSSR KPI (t= 0.96 or 96% and s = 0.99897 or 99.897)

9. **Handover Success Rate-In (HOSR-I):** The threshold for HOSR-I is 96%; all values below this point are categorized as '0' or manifestation of a degraded service. There are 23,813 instances that are within the threshold point under this KPI.

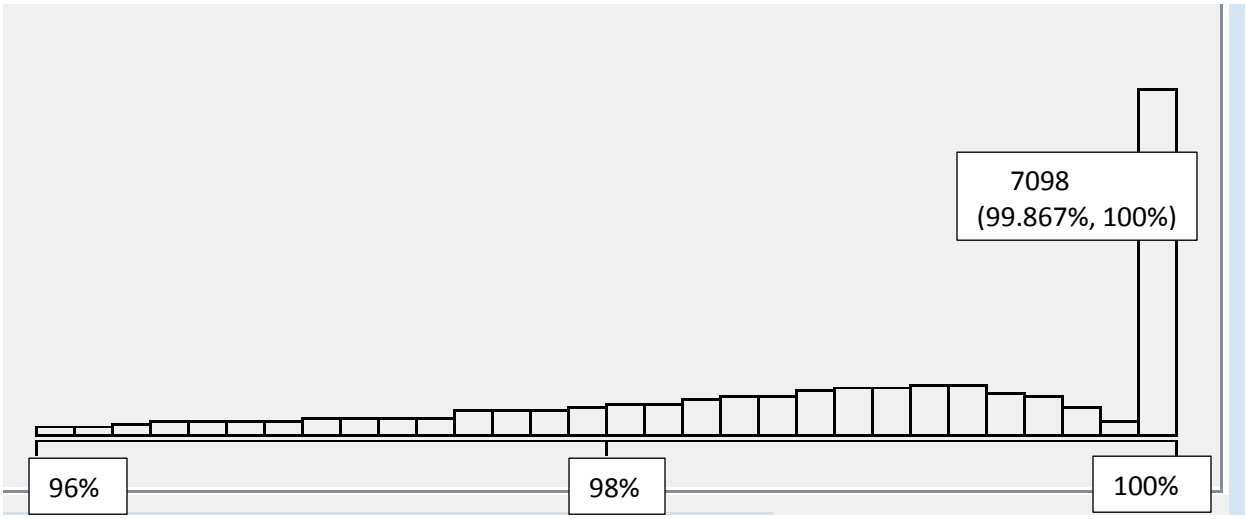


Figure 5.9 Distribution of the HOSR-I KPI data

As shown from the above HOSR-I KPI data distribution, starting from the threshold point (96%), the distribution increases slightly up to 99.867%, after this point the distribution indicates a considerable increase. Based on these concepts, discretization of the HOSR-I KPI data can be summarized by the following table.

0	1	2
HOSR-I KPI < 96%	96% <= HOSR-I KPI < 99.867	HOSR-I KPI >= 99.867

Table 5.14 Discretization of HOSR-I KPI (t= 0.96 or 96% and s = 0.99867 or 99.867)

10. **Handover Success Rate-Out (HOSR-O):** The threshold for HOSR-O is 96%; all values below this point are categorized as '0' or manifestation of a degraded service. There are 23,197 instances that are within the threshold point under this KPI.

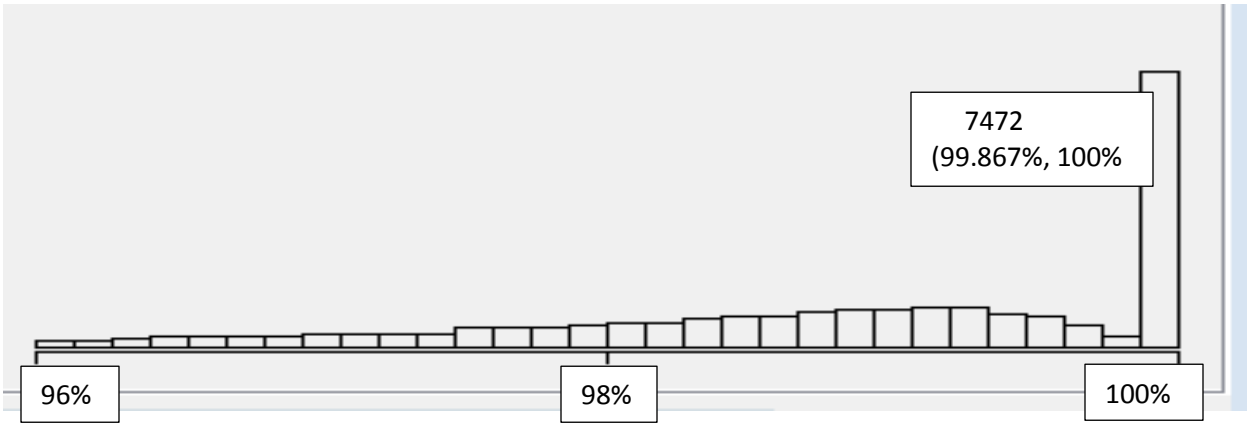


Figure 5.10 Distribution of the HOSR-O KPI data

As shown from the above HOSR-O KPI data distribution, starting from the threshold point (96%), the distribution increases slightly up to 99.867%, after this point the distribution indicates a considerable increase. Based on these concepts, discretization of the HOSR-O KPI data can be summarized by the following table.

0	1	2
HOSR-O KPI < 96%	96% <= HOSR-O KPI < 99.867	HOSR-O KPI >= 99.867

Table 5.15 Discretization of HOSR-O KPI (t= 0.96 or 96% and s = 0.99867 or 99.867)

The above discretization task based on the one day or 24 hour KPI data can be duplicated for the one week high traffic hour and one month KPI data, however, there is no significant variation in the distribution of the KPI data. Thus, for the purpose of this study, the above data points can also be used to discretize the one week high traffic hour and one month KPI data sets.

Sample KPI data before discretization is shown in Table 5.16 and the same KPI data after discretization is shown in Table 5.17.

CSR	SDCCH CR	TCH CR	DCR-S	SDCCH CDR	TCH CDR	HOSR	CSSR	HOSR-I	HOSR-O
98.76%	0.00%	0.00%	0.62%	0.00%	0.52%	100.00%	99.38%	100.00%	100.00%
100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	100.00%	100.00%	100.00%
93.33%	0.00%	0.00%	3.45%	0.00%	0.96%	100.00%	96.67%	100.00%	100.00%
100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	98.85%	100.00%	100.00%	97.50%
100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	100.00%	100.00%	100.00%
100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	100.00%	100.00%	100.00%
100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	100.00%	100.00%	100.00%
100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	97.50%	100.00%	100.00%	96.55%
100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	100.00%	100.00%	100.00%

Table 5.16 Sample KPI data before discretization

CSR	SDCCH CR	TCH CR	DCR-S	SDCCH CDR	TCH CDR	HOSR	CSSR	HOSR-I	HOSR-O
1	2	2	1	2	1	2	1	2	2
2	2	2	2	2	2	2	2	2	2
0	2	2	0	2	1	2	1	2	2
2	2	2	2	2	2	1	2	2	1
2	2	2	2	2	2	2	2	2	2
2	2	2	2	2	2	2	2	2	2
2	2	2	2	2	2	2	2	2	2
2	2	2	2	2	2	1	2	2	1
2	2	2	2	2	2	2	2	2	2

Table 5.17 Sample KPI data after discretization

5.2.5 Choosing the function of data mining

The purpose of the model derived by the data mining task involves identifying the importance of each KPI for the network quality of service, labeling the network quality of service based on values of the selected KPIs that appear concurrently with in a given period of time, clustering group of KPIs that appear concurrently with in a given period of time so that intra cluster similarity will be higher than inter cluster similarity. Consequently, classification and clustering are the data mining tasks covered in this study.

5.2.6 Choosing the data mining algorithm

The data mining algorithms selected for the tasks on this study such as classification, and clustering are covered in chapter 4. For, classification, J48 decision tree algorithm, Naïve Bayes and multilayer perception, and for clustering, k-means algorithms are applied. These algorithms become best matches for this study not only by their pros and cons described previously but also by different experimentations undertaken to choose the best algorithm per each data mining task.

5.2.7 Data Mining

After having the final data set at hand, the next task will be data mining. As indicated in Witten et.al. (2011), the final data set prepared for the data mining task doesn't specify which one of the attributes is going to be predicted. Thus, the same data set can be used to predict each attribute from the others in the case of classification, or to find association rules, or for clustering. In this regard, the data set of this study does not include a class label up to this point that aggregates each instances of the KPI.

On the other hand, Witten et. al. (2011) also discuss that when there is no specified class, clustering can be used to group items based on the natural proximity of the data. It may be followed by a second step of classification learning in which rules are learned regarding how new instances should be placed into the clusters. Likewise, after the first clustering experimentation, the classification task will be preceded by the class labeling.

As indicated from the outset, there are three data sets extracted from the network management system database, all of them are cleansed and reduced for the actual data mining task. After the preprocessing stage, the one day or 24 hour KPI data set contains 28,680 instances per each KPI (averaged per one hour granularity), the one week busy hour KPI data set contains 16,899 instances per each KPI (averaged per one hour granularity), and the one month KPI data set contains 37,510 instances per each KPI (averaged per one day granularity). Finally, all these data sets are consolidated in to one data set that contains 83,089 instances per each KPI.

In order to increase the representativeness of the data set, as much care as possible should be taken when samples are selected. In this regard, due to the nature of the application area, not only the effect of each KPI with in one full day or 24 hour should be visualized but also the

characteristics of each KPI during high traffic hour as well as its consistency for a certain period of time should be included so as to pave the way for a relatively good conclusion. This is also recommended by the domain experts in the application area. Henceforth, the consolidated data set will be used on the coming experiments.

Finally as discussed in Singh Y. & Chauhan S. (2009), four things are required in order to do the data mining task effectively: high-quality data, the "right" data, an adequate sample size and the right tool. In order to process this data set, there are various open source data mining tools such as KNIME, R, Orange, Natural Language Toolkit, RapidMiner, Weka, Rattle GUI … etc. with no particular order. For the purpose of this study, Weka 3.7.11 data mining tool will be used since it is platform independent as it is developed in java and its familiarity with the researcher.

5.3 Cluster Model

The raw data extracted from the network management system has no label. In this study clustering will be used to segment, rank and label the data based on the natural proximity of the values. These will facilitate the next classification experiment.

Weka has four different cluster modes: use training set (default), supplied test set, percentage split, and classes to clusters evaluation modes. In this study the default mode, use training set has been used.

The cluster model experiment is conducted using simple k-means clustering algorithm by different parameters for different number of clusters, K= 3, 4, and 5 as well as different seed values, S = 2, 3, and 5 on ten attributes containing 83,089 instances per each attribute (KPI). This experiment is conducted in two phases based on the distance function; Euclidean and Manhattan distance by tuning the parameters described in Table 5.18.

Parameter	Description
Seed Value	The random number seed to be used.
Distance Function	The distance function used for instances comparison (the default is Euclidean Distance).
Number of Cluster (K)	Used to set the number of clusters

Table 5.18 Description of parameters to be tuned in cluster modeling

5.3.1 Experiment 1

The result of experiment 1 using the Euclidean distance function and tuning the parameters described in Table 5.18 to find the best clustering model is summarized by Table 5.19.

Seed value	K	Cluster Distribution of Instances					Within cluster sum of squared errors	No of iterations
		Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5		
2	3	18343 (22%)	8377 (10%)	56369 (68%)			153112.0	4
	4	15034 (18%)	8366 (10%)	50124 (60%)	9565 (12%)		129682.0	4
	5	14941 (18%)	8328 (10%)	28299 (34%)	9565 (12%)	21956 (26%)	107726.0	4
3	3	34932 (42%)	16861 (20%)	31296 (38%)			165654.0	4
	4	33035 (40%)	9193 (11%)	32451 (39%)	8410 (10%)		152319.0	3
	5	32956 (40%)	7997 (10%)	26543 (32%)	7740 (9%)	7853 (9%)	112531.0	3
5	3	9038 (11%)	16062 (19%)	57989 (70%)			152014.0	3
	4	9035 (11%)	14946 (18%)	52727 (63%)	6381 (8%)		141488.0	3
	5	8753 (11%)	12908 (16%)	46962 (57%)	6106 (7%)	8360 (10%)	125909.0	3

Table 5.19 Summary of experiment 1 using Euclidean Distance Function

As shown from Table 5.19, the best clustering model of the Euclidean distance function is the one with lower 'within cluster sum of squared errors', which is having a seed value of 2 and 5 number of clusters. The clustering result of this model is described in the following Table 5.20:

Distribution of Instances	CSR	SDCCH-CR	TCH-CR	DCR	SDCCH-CDR	TCH-CDR	HOSR	CSSR	HOSR-I	HOSR-O
Cluster 1 14941 (18%)	1	2	2	1	1	1	0	1	0	0
Cluster 2 8328 (10%)	2	2	2	2	2	2	2	2	2	2
Cluster 3 28299 (34%)	1	2	2	1	1	1	1	1	1	1
Cluster 4 9565 (12%)	0	0	0	1	1	1	1	0	1	1
Cluster 5 21956 (26%)	1	1	2	1	1	1	1	1	1	1

Table 5.20 Clustering results of the best model in Euclidean distance function (K=5, seed value=2)

As it can be seen from the above Table 5.20, the algorithm clusters the data set based on the natural proximity of the discretized values. As indicated previously, the discretization of each attribute has its own concept hierarchy that would be inherited by the clusters segmentation. These clusters should be ranked based on the relative importance of the discretized values in each category in the context of the application area. Table 5.21 shows the ranking of each cluster with the corresponding description:

Rank	Cluster No	Description
1	**Cluster 2**	This category contains KPI values that are close to the top most or ideal value. Only 10% of the total data set is categorized here since it is difficult to achieve for network elements such a perfect result.
2	**Cluster 3**	Most of the KPI values under this category are within the threshold point with the exception of two KPIs that have best value.
3	**Cluster 5**	Most of the KPI values under this category are within the threshold point with the exception of one KPI that has best value.
4	**Cluster 1**	Most of the KPI values under this category are within the threshold point with the exception of two KPIs that are below the threshold point
5	**Cluster 4**	More KPI values are below the threshold point in reference to the previous clusters.

Table 5.21 Ranking of each cluster

The 'Within cluster sum of squared error (SSE)' of the best model using Euclidean distance function is still higher, it would be better to conduct another experiment. The previous parameter tuning task remains the same, it is better to search for a better cluster model by changing the distance function from Euclidean to Manhattan as shown in Experiment 2.

5.3.2 Experiment 2

The second experiment is conducted with every details of the first experiment except the distance function is Manhattan, which has been Euclidean in the first experimentation.

Seed value	K	Cluster Distribution					Within cluster sum of squared errors	No of iterations
		Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5		
2	3	18343 (22%)	8377 (10%)	56369 (68%)			153112.0	4
	4	15034 (18%)	8366 (10%)	50124 (60%)	9565 (12%)		129682.0	4
	5	14941 (18%)	8328 (10%)	28299 (34%)	9565 (12%)	21956 (26%)	107726.0	4
3	3	34932 (42%)	16861 (20%)	31296 (38%)			165654.0	4
	4	33035 (40%)	9193 (11%)	32451 (39%)	8410 (10%)		152319.0	3
	5	32956 (40%)	7997 (10%)	26543 (32%)	7853 (9%)	7740 (9%)	112531.0	3
5	3	9038 (11%)	16062 (19%)	57989 (70%)			152014.0	3
	4	9035 (11%)	14946 (18%)	52727 (63%)	6381 (8%)		141488.0	3
	5	8753 (11%)	12908 (16%)	46962 (57%)	6106 (7%)	8360 (10%)	125909.0	3

Table 5.22 Summary of experiment 2 using Manhattan Distance Function

As shown in Table 5.22, the best model using Manhattan distance function is the same as the one that has been tested using Euclidean distance function in both the input parameters tuned and the final result found including the distribution of instances on each cluster. Moreover, the 'Within cluster sum of squared error (SSE)' value and the iteration is also the same as the experiment 1 best model. As a result, the ranking of clusters will have the same order. Nevertheless, in order to differentiate the best model, it is better to refer the other parameter called 'Time taken to build model (full training data)", which is 1.84 seconds in the case of Manhattan Distance and 1.43 seconds for Euclidean Distance. Consequently, it is possible to consider the model built with Euclidean distance function as a worth splitting best model in-line with semantics of the data.

5.3.3 Evaluation of the Discovered Knowledge

Whatever a model is built, it would be useless unless and otherwise interpreted in reference with the application domain, which would make it understandable to the human user. In order to have

the best interpretation, one should not only examine the result of the clustering model but also refer the domain experts in the application area so as to confirm the applicability of the model built in the real situation. In this regard, the final cluster model of this experiment is tabulated in rank and a discussion is made with domain experts in the application area of mobile network optimization and interpreted accordingly.

Attributes	Cluster 2	Cluster 3	Cluster 5	Cluster 1	Cluster 4
CSR	2	1	1	1	0
SDCCH-CR	2	2	1	2	0
TCH-CR	2	2	2	2	0
DCR	2	1	1	1	1
SDCCH-CDR	2	1	1	1	1
TCH-CDR	2	1	1	1	1
HOSR	2	1	1	0	1
CSSR	2	1	1	1	0
HOSR-I	2	1	1	0	1
HOSR-O	2	1	1	0	1
Concept Hierarchy	1st Rank Better Quality	2 nd Rank Good Quality	3 rd Rank Fair Quality	4 th Rank Poor Quality	5 th Rank Bad Quality

Table 5.23 Ranked clusters of the selected cluster model

As shown in Table 5.23, Cluster 2 is ranked first (Better Quality) as all of its values are categorized under the top discretized group. On Cluster 3, which is ranked second (Good Quality), most of the KPI values are categorized under the normal values of the discretized group except the two KPIs that are categorized under the top discretized group and in Cluster 3, all values are the same as Cluster 1 except one KPI that do not have any change in the first three clusters. In the perspective of domain experts in the mobile network optimization, among the ten KPIs taken for this study, Call Setup Success Rate (CSSR) is a decisive KPI that its success factor is very much dependent on the success of two logical channels, SDCCH-CR and TCH-CR. The above ranked clusters also indicate, the KPI discretization group for these two KPIs in the 1st rank (Better Quality) and the 2nd rank (Good Quality) is the same, and the 3rd rank (Fair Quality) allows the SDCCH-CR to be in the normal discretized group than the TCH-CR. In the real situation, SDCCH-CR is not allowed to goes beyond the threshold point. This is because the first

resource that should be allocated for a subscriber is SDCCH since it is mandatory for call establishment, so that it should be available even in a very congested network environment.

If there is a considerable deviation between the CSR and the CSSR, it is an indication of a remarkable DCR so that the KPI value for CSR should not deviate much from the CSSR. In reference with the best cluster model selected, the CSSR value from rank 1 to rank 5 is 2,1,1,1,0 respectively and that of CSR is the same as the CSSR, which is 2,1,1,1,0. This shows the value of CSSR and CSR with in the same cluster have a value that fall under the same discretized group, which indicates the KPI values of CSSR and CSR are consistent in their respective cluster.

In the 4th ranked cluster (Poor Quality), HOSR, HOSR-I, and HOSR-O are beyond the threshold limit, however the rest KPIs in this cluster are within the desired range. In the 5th ranked cluster (Bad Quality), SDCCH-CR, TCH-CR, CSSR and the CSR are under the threshold point. What makes the 4th ranked cluster better than the 5th ranked cluster is that it only affects the HOSR KPIs that are related to the mobility nature of the network. In other words, the fourth ranked cluster only affects the moving customers but normal for the rest. In the 5th ranked cluster the negative impact on SDCCH-CR and TCH-CR affects the value of CSSR which in turns affect the value of the CSR. This will again confirms the dependency of CSSR on the values of SDCCH-CR and TCH-CR as described previously.

5.4 Classification Model

In the previous experiments, the best cluster model is selected and examined with the domain experts' knowledge in the application area. It would be logical to consider the cluster categorization created by this clustering model for the experimentation of the classification model, since the model worth splits the data set based on its natural proximity.

In this study, experimentation of classification model is conducted using three different algorithms: J48 decision tree classifier, Naïve Bayes classifier, and multilayer perception classifier. These algorithms are experimented by tuning different parameters in Weka to get the best classification model that can best classify the unseen data. Thus, randomly extracted and preprocessed separate data sets of 8478 instances to train and test the model and 4240 instances

to evaluate the classification accuracy of the selected models of each classifier have been prepared.

Among the four test options in Weka tool, 10 fold cross validation and percentage split have been used on this experiment to build and test as well as a supplied test set option to evaluate the classification model using a separate class labeled data set based on the selected cluster model. Thus, the labels can be taken as dependent variable whereas the KPIs (attributes) are independent variables.

In order to select attributes, 'GainRatioAttributeEval' and 'InfoGainAttributeEval' evaluators and a 'Ranker' search method is applied in the Weka attribute selection function as shown in Table 5.24.

Evaluator	Search	Selected / Ranked Attributes
GainRatioAttributeEval	Ranker	CSR, SDCCH-CR, CSSR, HOSR
InfoGainAttributeEval	Ranker	CSR, SDCCH-CR, HOSR, CSSR

Table 5.24 Attribute selection in Weka

When the first four attributes are considered, both evaluators select similar attributes regardless of the rank. These attributes could represent the rest attributes since one is a function aggregation of the other based on the KPI formulas (Appendix 1). Thus, these attributes have been applied in subsequent experiments.

5.4.1 J48 Decision Tree Classifier

In order to come up with the best J48 classification model, both the post pruning and pre pruning methods are implemented. These pruning mechanisms are labeled in Weka as ConfidenceFactor and MinNumObj respectively. In this study these two parameters shown on Table 5.25 are tuned for different values including the default so as to optimize the classification model.

Parameter	Description	Default value
ConfidenceFactor (CF)	The confidence factor used for pruning (smaller values incur more pruning)	0.25
MinNumObj (MNO)	The minimum number of instance per leaf	2

Table 5.25 Description of parameters to be tuned in J48 classification modeling

This experiment is conducted in the J48 decision tree using the 10 fold cross validation and the percentage split classification test option in Weka, with different ConfidenceFactor (CF) and MinNumObj (MNO) values including the default parameters shown in Table 5.24. The default value of percentage split, which is 66% for training and 34% for testing have been used. A data set of four selected attributes and 8478 instances has been used in this experiment. The results in both test options are presented in Table 5.26 so as to compare and select the best classification model of the J48 classification algorithm.

Tuned Parameters	Test Option	Number of leaves	Size of the tree	Time taken to build model	Classified Instances	
					Correctly	Incorrectly
Default: CF=0.25 MNO=2	10 fold cross validation	19	28	0.05 Seconds	7115 83.9231 %	1363 16.0769 %
	Percentage split	19	28	0.04 Seconds	2433 84.3913 %	450 15.6087 %
CF=0.25 MNO=5	10 fold cross validation	17	25	0.03 Seconds	7114 83.9113 %	1364 16.0887 %
	Percentage split	17	25	0.02 Seconds	2432 84.3566 %	451 15.6434 %
CF=0.75 MNO=2	10 fold cross validation	25	37	0.09 Seconds	7118 83.9585 %	1360 15.5741 %
	Percentage split	25	37	0.34 Seconds	2434 84.4259 %	449 15.5741 %
CF=1.0 MNO=2	10 fold cross validation	25	37	0.55 Seconds	7118 83.9585 %	1360 15.5741 %
	Percentage split	25	37	0.71 Seconds	2434 84.4259 %	449 15.5741 %

Table 5.26 Summary of experiment for the J48 algorithm using various parameter setting

As we can see from the above table, different parameters are tuned in order to optimize the J48 classifier. On this experiment, the J48 decision tree algorithm has a better classification accuracy and less time to build the model when MinNumObj = 2 and ConfidenceFactor = 0.75 with percentage split and this model can be selected as the best classification model to represent the J48. Snap shoot of detailed summary of result is attached in Appendix 2. The detailed predictive accuracy based on the evaluation on unseen data is also attached in Appendix 7.

Actual	Predicted					Total	Correctly Classified
	BeterQ	GoodQ	FairQ	PoorQ	BadQ		
BeterQ	340	0	0	0	0	340	100.0000%
GoodQ	91	546	0	0	4	641	85.1794%
FairQ	0	0	520	0	0	520	100.0000%
PoorQ	46	61	63	335	90	595	56.3025%
BadQ	0	48	10	36	693	787	88.0559%
Total						2883	84.4259%

Table 5.27 Confusion matrix for the selected J48 classifier (CF = 0.75, MNO = 2, and test option = percentage split)

As shown in Table 5.27, the selected classifier correctly classifies BeterQ and FairQ in to their class with an accuracy of 100%. It has the least classification accuracy for PoorQ. The classification accuracy of GoodQ and BadQ is close to the overall classification accuracy of the classifier.

5.4.2 The Naïve Bayes Classifier

The second classification model experiment is conducted using the Naïve Bayes statistical classifier. The Weka default classification test option, which is 10 fold cross validation and the percentage split with the default distribution of instances, 66% for training and 34% for testing are used. The following table summarizes the result of the experiment using this classifier in both classification test options.

Test Option	Time taken to build model	Classified Instances	
		Correctly	Incorrectly
10 fold cross validation	0.02 seconds	7013 (82.72 %)	1465 (17.28 %)
Percentage split	0.01 seconds	2397 (83.1426 %)	486 (16.8574 %)

Table 5.28 Summary of experiments for Naïve Bayes classifier

As shown from the above summary of experiments, the model with the 10 fold cross validation elapses less time to build the model and has a better correctly classified instances percentage than the model with the other test option. So that, the model with the percentage split test option could represent the best Naïve Bayes classifier in this experiment.

Actual	Predicted					Total	Correctly Classified
	BeterQ	GoodQ	FairQ	PoorQ	BadQ		
BeterQ	340	0	0	0	0	340	100.0000%
GoodQ	91	546	0	0	4	641	85.1794%
FairQ	0	0	508	12	0	520	97.6923%
PoorQ	46	61	60	328	100	595	55.1261%
BadQ	0	48	10	54	675	787	85.7687%
Total						2883	83.1426%

Table 5.29 Confusion matrix for the selected Naïve Bayes classifier

As shown in Table 5.29, the Naïve Bayes classifier has the best classification result for the BeterQ, where all KPIs have best value which indicates a network with relatively best QoS. And it has the least classification accuracy for the PoorQ, which is a network with limited mobility. Detailed summary of the result is attached in Appendix 3.

5.4.3 Multilayer Perception Classifier

The last classification model experiment examines the applicability of neural network to classify mobile network QoS KPIs based on the cluster categorization that has been selected in the previous cluster model experiments. Multilayer perception (MLP) classifier is a neural network classifier the classify instances using backpropagation. In order to come up with the best MLP model, the Weka tool has various setups some of them are described in Table 5.30.

Parameter	Description
Learning Rate	Learning Rate for the backpropagation algorithm. (Value should be between 0 - 1, Default = 0.3).
Hidden Layer	The hidden layers to be created for the network. (Value should be a list of comma separated Natural numbers or the letters 'a' = (attribs + classes) / 2, 'i' = attribs, 'o' = classes, 't' = attribs + classes) for wildcard values, Default = a). Comma separated numbers for nodes on each layer
GUI	GUI will be opened.

Table 5.30 Description of parameters to be tuned in MLP classification modeling

This experiment is conducted on the basis of two classification test options, 10 fold cross validation and percentage split. The default value of percentage split, which is 66% for training and 34% for testing have been used. A data set of four attributes selected by Weka attribute selection function with 8478 instances has been used. It is also tried to optimize the classification model through parameter setup of the ‘Hidden Layer’ and ‘Learning Rate’ that are specifically implemented on this study. Comparison of best model is performed in reference with the time taken to build the model and the percentage accuracy of correctly classified instances.

Parameter Setup	Test Option	Time taken to build model	Classified Instances	
			Correctly	Incorrectly
Hidden Layers = 4 Learning Rate = 0.3 Seed = 0	10 fold cross validation	13.05 Seconds	7103 83.7816 %	1375 16.2184 %
	Percentage split	13 Seconds	2425 84.1138 %	458 15.8862 %
Hidden Layers = 3 Learning Rate = 0.1 Seed = 10	10 fold cross validation	10.84 Seconds	7103 83.7816 %	1375 16.2184 %
	Percentage split	10.80 Seconds	2427 84.1831 %	456 15.8169 %
Hidden Layers = 5 Learning Rate = 0.1 Seed = 100	10 fold cross validation	15.07 Seconds	7123 84.0175 %	1355 15.9825 %
	Percentage split	15.21 Seconds	2426 84.1485 %	457 15.8515 %
Hidden Layers = 1 Learning Rate = 0.3 Seed = 0	10 fold cross validation	6.22 Seconds	5727 67.5513 %	2751 32.4487 %
	Percentage split	6.23 Seconds	2177 75.5116 %	706 24.4884 %
Hidden Layers = 5 Learning Rate = 0.1 Seed = 2	10 fold cross validation	15.13 Seconds	7077 83.4749 %	1401 16.5251 %
	Percentage split	15.17 Seconds	2435 84.4606 %	448 15.5394 %
Hidden Layers = 6 Learning Rate = 0.1 Seed = 3	10 fold cross validation	15.31 Seconds	7109 83.8523 %	1369 16.1477 %
	Percentage split	17.42 Seconds	2434 84.4259 %	449 15.5741 %
Hidden Layers = 6 Learning Rate = 0.1 Seed = 2	10 fold cross validation	15.38 Seconds	7086 83.581 %	1392 16.419 %
	Percentage split	15.23 Seconds	2436 84.4953 %	447 15.5047 %

Table 5.31 Summary of experiments for Multilayer Perception classifier

As shown from Table 5.31, the best MLP classification model in this experiment that have the highest classification accuracy is the one with Hidden Layers = 6, Learning Rate = 0.1 and Seed = 2 using percentage split test option. The selected MLP classifier classifies 84.4259 % of 8478 KPI records correctly in to their class. Detailed summary of the result is attached in Appendix 4.

Actual	Predicted					Total	Correctly Classified
	BeterQ	GoodQ	FairQ	PoorQ	BadQ		
BeterQ	340	0	0	0	0	340	100.0000%
GoodQ	91	546	0	0	4	641	85.1794%
FairQ	0	0	520	0	0	520	100.0000%
PoorQ	46	61	63	346	79	595	58.1513%
BadQ	0	48	10	45	684	787	86.9123%
Total						2883	84.4953%

Table 5.32 Confusion matrix of the best MLP model (Hidden Layers = 6, Learning Rate = 0.1, Seed = 2)

Table 5.32 indicates the classification accuracy of the selected MLP model per each class. It has a classification accuracy of 100% for BeterQ and FairQ.

5.4.4 Comparison of J48, Naïve Bayes, and Multilayer Perception Models

In order to select a data mining model for classification tasks in the context of this study, it is necessary to evaluate the selected best model from J48 decision tree algorithm, Naïve Bayes and Multilayer perception (MLP) classifiers. Each model could basically be evaluated based on their classification accuracy though there are different methods from literatures to compare classifiers built on different classification algorithms.

Classifier	Test options	Parameter setup	Time to build the model	Classification accuracy
J48 decision tree	Percentage Split	CF=0.75 MNO=2	0.34 Seconds	2434 84.4259 %
Naïve Bayes	Percentage Split	Default parameters	0.01 seconds	2397 83.1426 %
MLP	Percentage Split	Hidden Layers = 6 Learning Rate = 0.1 Seed = 2	15.23 Seconds	2436 84.4953 %

Table 5.33 Comparison of classification accuracy for the three classifiers

As indicated in Table 5.33, based on the classification accuracy, MLP classifier shows the highest classification accuracy. It accurately classifies 84.4953% of KPI records in to their right QoS label. Consequently, the model built on MLP is the best model to classify KPI instances in to their correct class when it is compared to the other two classifiers.

As indicated from the inception, a separate test set of data set size 4240 instances using Weka selected attributes is provided to test the predictive accuracy of the selected classifier for unseen data. Table 5.34 indicates the classification accuracy of the three classifiers based on the evaluation for unseen data.

Classifier	Test options	Correctly Classified	Incorrectly Classified
J48 decision tree	Supplied Test Set	3567 84.1274 %	673 15.8726 %
Naïve Bayes	Supplied Test Set	3525 83.1368 %	715 16.8632 %
MLP	Supplied Test Set	3572 84.2453 %	668 15.7547 %

Table 5.34 Classification accuracy of the three classifiers on a separate data set

Table 5.35 indicates the detailed accuracy by class of the selected MLP model when it is evaluated by the separate data set of 4240 instances, which is unseen data. The detailed result of the evaluation on a separate test set of the selected MLP classifier is indicated in Appendix 9.

	TP Rate	**FP Rate**	**Precision**	**Recall**	**F-Measure**	**MCC**	**ROC Area**	**PRC Area**	**Class**
	1	0.009	0.466	1	0.636	0.679	0.995	0.466	BeterQ
	0.971	0.102	0.857	0.971	0.91	0.853	0.951	0.866	GoodQ
	1	0.022	0.845	1	0.916	0.909	0.99	0.86	FairQ
	0.564	0.017	0.929	0.564	0.702	0.655	0.87	0.786	PoorQ
	0.887	0.069	0.783	0.887	0.832	0.783	0.949	0.896	BadQ
Weighted Average	**0.842**	**0.062**	**0.856**	**0.842**	**0.833**	**0.787**	**0.933**	**0.846**	

Table 5.35 Detailed accuracy by class for the selected MLP model

Table 5.36 indicates a sample on how the selected MLP model classifies QoS based on the unseen test data which is not labeled in comparison with the actual label. The question marks in the predicted side indicate the value of the QoS is not known or the data is not labeled.

Actual					Predicted			
CSR	SDCCH-CR	CSSR	HOSR	QoS	actual	predicted	error	prediction
1	2	1	1	GoodQ	1:?	2:GoodQ		0.866
1	2	1	1	GoodQ	1:?	2:GoodQ		0.866
1	1	1	0	PoorQ	1:?	4:PoorQ		0.951
1	1	1	1	FairQ	1:?	3:FairQ		0.87
1	2	1	0	PoorQ	1:?	4:PoorQ		0.934
0	0	0	0	BadQ	1:?	5:BadQ		0.564
1	2	1	1	GoodQ	1:?	2:GoodQ		0.866
1	0	1	1	BadQ	1:?	5:BadQ		0.957
1	2	1	1	GoodQ	1:?	2:GoodQ		0.866
1	2	1	1	GoodQ	1:?	2:GoodQ		0.866
1	2	1	1	GoodQ	1:?	2:GoodQ		0.866
1	2	1	0	PoorQ	1:?	4:PoorQ		0.934
1	2	1	1	GoodQ	1:?	2:GoodQ		0.866
1	1	1	1	FairQ	1:?	3:FairQ		0.87

Table 5.36 Sample values indicating actual versus predicted QoS.

5.4.5 Evaluation of the discovered knowledge

On the first experiment, it has been tried to create the best classification model from the J48 decision tree algorithm by testing it on different values of post-pruning and pre-pruning parameters. As a result, the model built on this classification algorithm could accurately classify 84.4259% of KPI records in to their right class to the best of these two parameters. The knowledge extracted from the J48 decision tree classifier could also be helpful to generalize the category of QoS based on the selected attributes.

The following rules are important rules taken by traversing through the J48 decision tree (attached in Appendix 6). The semantics of these rules with the real environment is confirmed by domain experts.

If CSR=2 and HOSR=2 and CSSR=2 then BeterQ
If CSR=1 and SDCCH_CR=2 and HOSR=1 and CSSR=1 or CSSR=2 then GoodQ
If CSR=1 and SDCCH_CR=2 and HOSR=2 then GoodQ
If CSR=1 and SDCCH_CR=1 and HOSR=1 and CSSR=1 then FairQ
If CSR=1 and SDCCH_CR=1 and HOSR=1 CSSR=1 then FairQ
If CSR=1 and SDCCH_CR=1 and HOSR=0 then PoorQ
If CSR=1 and SDCCH_CR=2 and HOSR=0 then PoorQ
If CSR=1 and SDCCH_CR=1 and HOSR=0 then PoorQ
If CSR=2 and HOSR=0 and 2 then PoorQ
If CSR=0 and HOSR=0 and SDCCH_CR=0 then BadQ
If CSR=1 and SDCCH_CR=0 then BadQ
If CSR=1 and SDCCH_CR=0 then BadQ

The second experiment is conducted on the Naïve Bayes classification algorithm that results the least classification accuracy of all the experimented classifiers, which is 83.1426 %. It has the best classification accuracy for KPI instances classified in the 1st ranked cluster or labeled as 'Better Quality', which is 100%.

It takes longer time to build a multilayer perception classification model related to other classification algorithms in all experiment setups as it has been approved in the third experiment. Based on the experiments conducted on the MLP classifier on different values of Hidden Layer, Learning Rate, and Seed value, it has been shown that 84.4953 % classification accuracy can be achieved to the best of the indicated parameters. This classification accuracy is also the best of the other two classifiers, J48 decision tree and NaivBayes.

Chapter Six

6 Conclusion and Recommendations

6.1 Conclusion

The availability of data by itself do not acquire data mining as a quick fix, it should also be processed to make it suitable for the data mining task. In this regard, huge amount of data is generated in every aspect of the industry especially in telecommunications. Once the nature of the data is understood, it would be easy to call for the corresponding data mining task. In the context of telecommunications, such tasks include Customer Relationship Management (CRM), Fraud Detection, and Network Fault detection and isolation which is conducted up on the huge and complex data generated by the network as this study do.

This study tries to analyze the KPI data indicating the general quality of service (QoS) in a mobile network by applying different data mining technologies. The cluster model using the k-means algorithm with its corresponding parameter adjustment provides a worth splitting clusters based on the natural proximity of the KPI data, discretized as '0'or '1' or '2', related to the concept hierarchy. On the other hand, various experiments are conducted to identify the best classification model. Thus, the classification model built on MLP has the best accuracy relative to the J48 and the Naïve Bayes classification algorithm.

Among the KPIs studied, Call Success Rate (CSR) could measure an end to end performance of a mobile network since CSR indicates the success of a call from its initiation when Standalone Dedicated Control Channel (SDCCH) is allocated to establish a call; Traffic Channel (TCH) is assigned to hold the call until it comes to a deliberate termination which otherwise could be a dropped call. On the other hand the SDCCH and TCH KPIs decide the performance of the Call Setup Success Rate (CSSR) KPI since to set up a call both call establishment and call persistency resources are mandatory. Thus, the two logical channels, SDCCH and TCH, are crucial for the QoS experienced by the customer.

The clustering model built on the simple k-means algorithm provides a better understanding of the KPI data as it cluster the instances based on their natural proximity. Moreover, the

interpretation is very close to the real mobile network optimization knowledge of the domain experts. So that it is a suitable model to study the real nature and concurrency of the mobile network general QoS KPIs.

The multilayer perception classification model, which is an implementation of neural network, is the best model in classifying the KPIs to their ranked cluster labeled as 'Better Quality', 'Good Quality', 'Fair Quality', 'Poor Quality' and 'Bad Quality'.

The rules taken by traversing through the J48 decision tree are important rules that could be used to generalize the network quality of service in the real situation.

Effective analysis of GSM networks is currently challenging because of large volume of data collected from network elements and evolution towards better technologies might further increase the size and complexity of data. It is essential to apply data mining to extract the relevant information to a level which can be easily managed.

Finally, as there is no cut and dried data set available for a data mining task, different challenges are faced from data preprocessing through data transformation up to the data mining task. First of all, there is no split point between the threshold (t) and the ideal (maximum desirable) values for each KPI. Secondly, the data set taken from the network management system is not labeled. It needs a considerable time and strategy to do this task. And lastly, the large data set provided for the data mining task not only needs a considerable computational resource but also challenges the efficiency of the algorithm. Most of the challenges are vanquished by this research which can be considered as strength.

6.2 Recommendation

Based on the findings, the following recommendations are presented:

- The data mining tasks performed on this specific study revolves around clustering and classification. The cluster model experiment is undertaken based on the simple k-means algorithm, where the best cluster model selection is on the basis of parameter adjustment. On the other hand, the Multilayer Perception classification model is selected relative to J48 and Naïve Bayes classification algorithms. However, other clustering and classification algorithms might reveal even a better accuracy.
- Even though the research is done for academic achievements, the output can be used for a better understanding of different KPIs and their relationship as well as to generalize network quality of service based on important rules. These can be applied in the mobile network optimization task.
- The concept of QoS is not only a big issue in a second generation (2G) network, but also it is the main concern of the third generation (3G), as well as the fourth generation (4G) network. Moreover, this study is concerned about the general quality of service KPIs in the mobile telecommunication network; there are also other KPIs that are specifically designed to measure the service quality of data, internet, and others. These might leave a room to conduct further studies

References

Ali, M. Shehzad, A., & Akram, M. (2010). Radio Access Network Audit & Optimization in GSM (Radio Access Network Quality Improvement Techniques). *International Journal of Engineering & Technology IJET-IJENS Vol: 10 No: 01*

Almeida, L. (1997). *Handbook of Neural Computation release.* IOP Publishing Ltd and Oxford University Press

Breiman, L., Friedman, J., Olshen, R., Stone, C. (1984). *Classification and Regression Trees*. Wadsworth International Group.

Bouckaert, R., Frank, E., Hall, M., Kirkby, R., Reutemann, P., Seewald, A., Scuse, D. (2014). Weka (Version 3-7-11) [Computer software]. University of Waikato: Hamilton.

Carvalho, F. & Magedanz, T. (2007). *Telecommunication Systems and Technologies.* Berline: Encyclopedia of Life Support System (ELSS)

Chandra, P. (2005). *Bulletproof wireless security: GSM, UMTS, 802.11 and Ad Hoc Security.* Elsevier Inc.

Chapman, P. (2000). *CRISP-DM 1.0: Step-by-step data mining guide*. SPSS Inc.

Cios, K., Pedrycz, W., Swiniarski, R., Kurgan, L. (2007). *Data mining: A knowledge discovery approach*. Springer Science & Business Media, LLC

Clemm, A. (2007). *Network management fundamentals*. Cisco Systems, Inc.

Dunlop, J. & Smith, D, (2000). *Telecommunications engineering, Third edition*. Chapman & Hall

Esling, P. & Agon, C. (2012). *Time-Series Data Mining.* ACM Comput. Surv. 45(1), Article 12

ethio-telecom (2012). Company profile.

ethio-telecom (November 2013). Press release. Retrieved from http://www.ethiotelecom.et/news/news.php?id=88

ethio-telecom (September 2011). Press release. Retrieved from http://www.ethiotelecom.et/press/news.php?id=37

ethio-telecom (September 2012). Press release. Retrieved from http://www.ethiotelecom.et/press/news.php?id=74

ETSI (2004). *Speech Processing, Transmission and Quality Aspects (STQ); QoS aspects for popular services in GSM and 3G networks; Part 6: Post processing and statistical methods*. Technical Specification, TS, 102 250-6 V1.2.1

ETSI (2010). *Key Performance Indicators (KPI) for UMTS and GSM. Technical Specification, 3GPP TS 32.410 version 9.0.0 Release 9.*

Fayyad, U., Piatetsky, G., & Smyth, P. (1996b). *From Data Mining to Knowledge Discovery in Databases.* American Association for Artificial Intelligence.

Fayyad, U., Piatetsky, G., & Smyth, P. (1996c). Mining Scientific Data. *Communications of the ACM, 39(11),pp. 51-57*

Fong, S. (2011). Data Mining for Resource Planning and QoS Supports in GSM Networks. *Journal of Emerging Technologies in Web Intelligence, Vol. 3, No. 2.*

Gebremeskal, G. (2006). *Data Mining Application in Supporting Fraud Detection on Ethio-Mobile Services.* (Masters Thesis, Addis Ababa University)

Gómez, G & Sánchez, R (eds), (2005). *End-to-End Quality of Service over Cellular Networks*. John Wiley & Sons Ltd

Gorunescu, F. (2011). *Data Mining: Concepts, Models and Techniques.* Springer

Haider, B., Zafrullah, M. & Islam, M. K. (2009). Radio Frequency Optimization & QoS Evaluation in Operational GSM Network. *Proceedings of the World Congress on Engineering and Computer Science, Vol I.*

Halonen, T. Romero, J. & Melero, J. (eds.), (2003). *GSM, GPRS and EDGE Performance: evolution towards 3G/UMTS, Second edition.* John Wiley & Sons Ltd.

Han, J. & Kamber, M. (2006). *Data Mining: Concepts and Techniques, Second Edition*. Elsevier Inc.

Hardy, C. (2001). *QoS: Measurement and evaluation of telecommunications quality of service*. Chichester: John Wiley & Sons

Harrington, P. (2012). *Machine learning in action*. Manning Publications

Horak, R. (2007), *Telecommunications and data communications handbook*. John Wiley & Sons

ITU (2013). World Telecommunication/ICT Indicators database. Retrieved from http://www.itu.int/en/ITU-D/Statistics/Pages/stat/default.aspx

ITU-CCITT (2007). *Quality of service and dependability vocabulary, Series E: Overall network operation, Telephone service, Service operation and human factors*, Geneva: ITU

ITU-T (2000). *TMN Management Functions, Series M: TMN and Network Maintenance: International Transmission Systems Telephone Circuits, Telegraphy, Facsimile, And Leased Circuits.* M.3400 Recommendation

Joseph, M. (2013). Data Mining and Business Intelligence Applications in Telecommunication Industry. *International Journal of Engineering and Advanced Technology (IJEAT), pp 2249 – 8958, Volume-2, Issue-3*

Kamber, M., Pei, J., & Han, J. (2011). *Data mining: Concepts and techniques, Third Edition.* Elsevier Inc.

Krose, V. & Smagt, P. (1996). *An Introduction to neural network.* The University of Amesterdam

Kumar, P., Anuradha, B., Naresh, V. (2004). Improvement Of Key Performance Indicators and QoS Evaluation in Operational GSM Network. *International Journal of Engineering Research and Applications (IJERA), Vol. 1, Issue 3, pp.411-417*.

Kumar, V., Tan, P., & Steinbach (2001), *Introduction to Data Mining.* CRC Press

Kumar, V., Tan, P., & Steinbach, M. (2001). *Introduction to data mining.* CRC Press, LLC

Kyriazakos, S. & Karetsos, G. (2004). *Practical radio resource management in wireless systems.* Artech House

Kyriazakos, S., Papaoulakis, N., Nikitopoulos, D., Gkroustiotis, E., Kechagias, C., Karambalis, C., & Karetsos, G. (2002*). A Comprehensive Study and Performance Evaluation of Operational GSM and GPRS Systems under Varying Traffic Conditions*. IST Mobile and Wireless telecommunications Summit, 2002, Greece

Laiho, J., Wacker, A. & Novosad, T. (eds.), (2006). *Radio network planning and optimization for UMTS, Second Edition*. John Wiley & Sons Ltd

Lehtim aki, P. (2008). *Data analysis methods for cellular network performance optimization.* (Docteral dissertation, Helsinki University of Technology).

Lempiäinen, J. and Manninen, M. (2002). *Radio interface system planning for GSM/GPRS/UMTS.* Kluwer Academic Publishers

Maimon, O. and Rokach, L.(eds.) (2010). *Data Mining and Knowledge Discovery Handbook. Second Edition*. Springer

Mariscal, G., Marba, O. & Fernandez, C. (2010). A Survey of Data Mining And Knowledge Discovery Process Models And Methodologies. *The Knowledge Engineering Review, Vol. 25:2, pp.137–166.*

Melaku, G. (2009). *Applicability of Data Mining Techniques to Customer Relationship Management (CRM): The Case of Ethiopian Telecommunication Corporation's (ETC) Code Division Multiple Access (CDMA) Telephone Service*. (Masters thesis, Addis Ababa University)

Mishra, A. (2004). *Fundamentals of cellular network planning and optimization: 2G/2.5G/3G... evolution to 4G*. John Wiley & Sons, Ltd

Multanen M., Kimmo Raivio, K., & Lehtim, P. (2006). *Hierarchical Analysis of GSM Network Performance Data*. Helsinki University of Technology.

Nadaf, M. & Kadam, V. (2013). *Data Mining in Telecommunication.*Volume-2, Issue-3, pp 2319 – 2526

Pitas, C. Chourdaki, K. Panagopoulos, A & Constantinou, P. (2011). QoS Mining Methods for Performance Estimation of Mobile Radio Networks. *10th Int'l Conf. on Measurement of Speech, Audio and Video Quality in Networks (MESAQIN).* Athens: National Technical University

Popoola, J. J., Megbowon, I. O., & Adeloye, V. S. A. (2009). Performance Evaluation and Improvement on Quality of Service of Global System for Mobile Communications in Nigeria. *Journal of Information Technology Impact, Vol. 9, No. 2, pp. 91-106*

Pressman, R. (2005). *Software Engineering: A Practitioner's Approach, 6th edition*, McGraw-Hill

Rahnema M., (2008). *UMTS Network planning, optimization, and inter-operation with GSM*. John Wiley & Sons

Rokach, L. & Maimon, O. (2008). *Data mining with decision trees: Theory and Applications*. World Scientific Publishing Co. Pte. Ltd.

Singh Y. & Chauhan S. (2009). Neural Networks in Data Mining. *Journal of Theoretical and Applied Information Technology*. Retreived from: www.jatit.org

Sorokosz, L. & Zieniutycz, W. (2012). *Artificial Neural Networks in Microwave Components and Circuits Modeling.* Przeglad Elektrotechniczny (Electrical Review)

Sumathi, S. & Sivanandam S. (2006). *Introduction to Data Mining and its Applications.* Springer

Tele Management Forum (2000). *Telecom Operations Map*. GB910

The Federal Democratic Republic of Ethiopia (2011). *Federal Negarit Gazeta, 17th, Year No. 11, Addis Ababa 28th January*

Tyrrell, S. (2000). *The many dimensions of the software processes.* ACM Crossroads 6(4), pp. 22–26.

Vehviläinen, V. (2004). *Data mining for managing intrinsic quality of service in digital mobile telecommunications networks.* (Doctoral thesis, Tampere University of Technology).

Ville, B. (2006). *Decision trees for business intelligence and data mining: Using SAS enterprise miner.* Cary, NC: SAS Institute Inc.

Weiss, G. (2009). *Data Mining in the Telecommunications Industry*. USA: Global Fordham University.

Williams, G (2011). D*ata mining with rattle and R: The art of excavating data for knowledge discovery.* Springer

Witten, I, Frank, E., and Hall, M. (2011). Data Mining Practical Machine Learning Tools and Techniques, Third Editio. , Morgan Kaufmann Publishers

Wu, *X*., Kumaret, V., Quinlanal, J. R., Ghosh, J., Yang, Q., & Motoda, H. (2007). *Top 10 algorithms in data mining*. London: Springer

Yang, Q. & Wu, X. (2006). 10 Challenging Problems in Data Mining Research. *International Journal of Information Technology & Decision Making Vol. 5, No. 4, pp. 597–604*, World Scientific Publishing Company

Ye, N. (ed.), (2003). *The handbook of data mining.* Lawrence Erlbaum Associates, Inc.

Yeshinegus, G. (2013). *Predictive Modeling for Fraud Detection in Telecommunications: The Case of Ethio-Telecom.* AAU, (Masters thesis, Addis Ababa University)

Zaki, M. & Meira, J. W. (2013). *Data Mining and Analysis: Fundamental Concepts and Algorithms*. Cambridge University Press

Zhang, Q. & Gupta, K. (2000). *Neural Network for RF and Microwave Design*. Artech House Publisher.

Zhao, Y. & Zhang, Y. (2007). *Comparison of decision tree methods for finding active objects*. Bejing: National Astronomical Observatories.

Appendices

Appendix 1: KPI Formulas based on measured parameters

S/no	KPI (%)	Formula
1	**CSR**	**((1-(A+B+C)/(D+E+F))*(1-G/H)*(I+J)/(K+L))*(1-((M+N)/(O+P+P+Q+R)))**
	A	Number of SDCCH seizure failure for assignment(Times)
	B	Number of signaling TCH/F seizure failure for assignment(Times)
	C	Number of signaling TCH/H seizure failure for assignment(Times)
	D	Number of SDCCH seizure attempts for assignment(Times)
	E	Number of signaling TCH/F seizure attempts for assignment(Times)
	F	Number of signaling TCH/H seizure attempts for assignment(Times)
	G	Number of SDCCH drops(Times)
	H	Number of SDCCH assignment success(Times)
	I	Number of voice TCH/F assignment success(Times)
	J	Number of voice TCH/H assignment success(Times)
	K	Number of voice TCH/F seizure attempts for assignment(Times)
	L	Number of voice TCH/H seizure attempts for assignment(Times)
	M	Number of TCH/F drops(Times)
	N	Number of TCH/H drops(Times)
	O	Number of signaling TCH/F assignment success for assignment(Times)
	P	Number of voice TCH/F assignment success(Times)
	Q	Number of voice TCH/H assignment success(Times)
	R	Number of signaling TCH/H assignment success(Times)
2	**SDCCH-CR**	**(A+B+C)/(D+E+F)**
	A	Number of SDCCH seizure failure for assignment(Times)
	B	Number of signaling TCH/F seizure failure for assignment(Times)
	C	Number of signaling TCH/H seizure failure for assignment(Times)
	D	Number of SDCCH seizure attempts for assignment(Times)
	E	Number of signaling TCH/F seizure attempts for assignment(Times)
	F	Number of signaling TCH/H seizure attempts for assignment(Times)
3	**TCH-CR**	**(A+B+C+D+E+F+G+H)/(I+J+K+L+M+N+O)**

	A	Number of voice TCH/F seizure failure for assignment(Times)
	B	Number of data TCH/F seizure failure for assignment(Times)
	C	Number of voice TCH/H seizure failure for assignment(Times)
	D	Number of data TCH/H seizure failure for assignment(Times)
	E	Number of voice TCH/F seizure failure for handover(Times)
	F	Number of data TCH/F seizure failure for handover(Times)
	G	Number of voice TCH/H seizure failure for handover(Times)
	H	Number of data TCH/H seizure failure for handover(Times)
	I	Number of voice TCH/F seizure attempts for assignment(Times)
	J	Number of data TCH/F seizure attempts for assignment(Times)
	K	Number of voice TCH/H seizure attempts for assignment(Times)
	L	Number of data TCH/H seizure attempts for assignment(Times)
	M	Number of voice TCH/F seizure attempts for handover(Times)
	N	Number of data TCH/F seizure attempts for handover(Times)
	O	Number of voice TCH/H seizure attempts for handover(Times)
	P	Number of data TCH/H seizure attempts for handover(Times)
4	**DCR**	**(A+B)/(C+D+E+F)**
	A	Number of TCH/F drops(Times)
	B	Number of TCH/H drops(Times)
	C	Number of signaling TCH/F assignment success for assignment(Times)
	D	Number of voice TCH/F assignment success(Times)
	E	Number of voice TCH/H assignment success(Times)
	F	Number of signaling TCH/H assignment success(Times)
5	**SDCCH-CDR**	**A/(B+C+D)**
	A	Number of SDCCH drops(Times)
	B	Number of SDCCH seizure attempts for assignment(Times)
	C	Number of signaling TCH/F seizure attempts for assignment(Times)
	D	Number of signaling TCH/H seizure attempts for assignment(Times)
6	**TCH-CDR**	**(A+B)/(C+D+E+F+G+H+I)**
	A	Number of TCH/F drops(Times)
	B	Number of TCH/H drops(Times)
	C	Number of voice TCH/F assignment success(Times)

	D	Number of data TCH/F assignment success(Times)
	E	Number of voice TCH/H assignment success(Times)
	F	Number of data TCH/H assignment success(Times)
	G	Number of BSC-controlled inter-cell incoming handover success(Times)
	H	Number of MSC-controlled incoming handover success(Times)
	I	Number of intra-cell handover success(Times)
7	**HOSR**	**(A+B+C)/(D+E+F+G+H+I+J+K+L+M+N+O+P)**
	A	Number of BSC-controlled inter-cell incoming handover success(Times)
	B	Number of MSC-controlled incoming handover success(Times)
	C	Number of intra-cell handover success(Times)
	D	Number of BSC-controlled inter-cell outgoing handover success(Times)
	E	Number of MSC-controlled outgoing handover success(Times)
	F	Number of BSC-controlled inter-cell incoming handover(Times)
	G	Number of BSC-controlled inter-cell incoming handover due to forced release(Times)
	H	Number of BSC-controlled inter-cell incoming handover due to queue(Times)
	I	Number of BSC-controlled inter-cell incoming handover due to forced handover(Times)
	J	Number of MSC-controlled incoming handover(Times)
	K	Number of MSC-controlled incoming handover due to forced release(Times)
	L	Number of times a service queues due to MSC-controlled incoming handover(Times)
	M	Number of MSC-controlled incoming handover due to forced handover(Times)
	N	Number of intra-cell handover(Times)
	O	Number of BSC-controlled inter-cell outgoing handover(Times)
	P	Number of MSC-controlled outgoing handover(Times)
8	**CSSR**	**(1-(A+B+C)/(D+E+F))*(1-G/H)*(I+J)/(K+L))**
	A	Number of SDCCH seizure failure for assignment(Times)
	B	Number of signaling TCH/F seizure failure for assignment(Times)
	C	Number of signaling TCH/H seizure failure for assignment(Times)
	D	Number of SDCCH seizure attempts for assignment(Times)
	E	Number of signaling TCH/F seizure attempts for assignment(Times)
	F	Number of signaling TCH/H seizure attempts for assignment(Times)

	G	Number of SDCCH drops(Times)
	H	Number of SDCCH assignment success(Times)
	I	Number of voice TCH/F assignment success(Times)
	J	Number of voice TCH/H assignment success(Times)
	K	Number of voice TCH/F seizure attempts for assignment(Times)
	L	Number of voice TCH/H seizure attempts for assignment(Times)
9	**HOSR-I**	**(A+B+C)/(D+E+F+G+H+I)**
	A	Number of BSC-controlled inter-cell incoming handover success(Times)
	B	Number of MSC-controlled incoming handover success(Times)
	C	Number of intra-cell handover success(Times)
	D	Number of BSC-controlled inter-cell incoming handover(Times)
	E	Number of MSC-controlled incoming handover(Times)
	F	Number of MSC-controlled incoming handover due to forced release(Times)
	G	Number of times a service queues due to MSC-controlled incoming handover(Times)
	H	Number of MSC-controlled incoming handover due to forced handover(Times)
	I	Number of intra-cell handover(Times)
10	**HOSR-O**	**(A+B+C)/(D+E+F)**
	A	Number of BSC-controlled inter-cell outgoing handover success(Times)
	B	Number of MSC-controlled outgoing handover success(Times)
	C	Number of intra-cell handover success(Times)
	D	Number of BSC-controlled inter-cell outgoing handover(Times)
	E	Number of MSC-controlled outgoing handover(Times)
	F	Number of intra-cell handover(Times)

Appendix 2: Summary of results for the selected J48 decision tree algorithm model

```
=== Summary ===

Correctly Classified Instances        2434               84.4259 %
Incorrectly Classified Instances       449               15.5741 %
Kappa statistic                          0.8033
Mean absolute error                      0.0999
Root mean squared error                  0.2211
Relative absolute error                 31.7867 %
Root relative squared error             55.6992 %
Coverage of cases (0.95 level)          98.9594 %
Mean rel. region size (0.95 level)      41.3736 %
Total Number of Instances             2883

=== Detailed Accuracy By Class ===

               TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
               1.000    0.054    0.713      1.000    0.832      0.821    0.973     0.713     BeterQ
               0.852    0.049    0.834      0.852    0.843      0.797    0.959     0.800     GoodQ
               1.000    0.031    0.877      1.000    0.934      0.922    0.985     0.879     FairQ
               0.563    0.016    0.903      0.563    0.694      0.661    0.876     0.758     PoorQ
               0.881    0.045    0.881      0.881    0.881      0.836    0.968     0.934     BadQ
Weighted Avg.  0.844    0.038    0.854      0.844    0.838      0.805    0.951     0.832

=== Confusion Matrix ===

   a   b   c   d   e   <-- classified as
 340   0   0   0   0 |   a = BeterQ
  91 546   0   0   4 |   b = GoodQ
   0   0 520   0   0 |   c = FairQ
  46  61  63 335  90 |   d = PoorQ
   0  48  10  36 693 |   e = BadQ
```

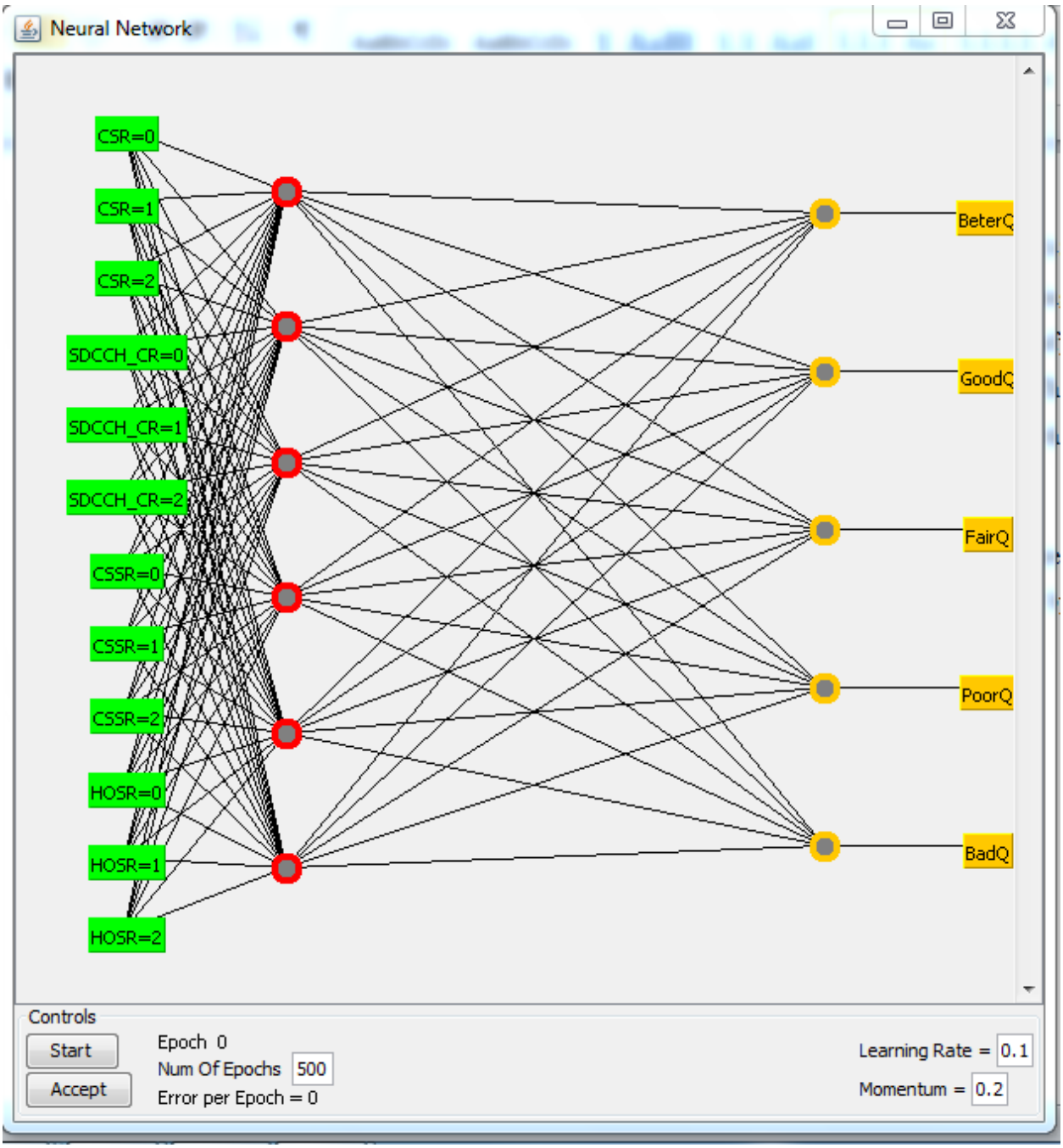
Appendix 3: Summary of results for the selected Naïve Bayes algorithm

```
=== Summary ===

Correctly Classified Instances        2397               83.1426 %
Incorrectly Classified Instances       486               16.8574 %
Kappa statistic                          0.7871
Mean absolute error                      0.0903
Root mean squared error                  0.2421
Relative absolute error                 28.7125 %
Root relative squared error             60.9955 %
Coverage of cases (0.95 level)          91.9875 %
Mean rel. region size (0.95 level)      32.7298 %
Total Number of Instances             2883

=== Detailed Accuracy By Class ===

               TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
               1.000    0.054    0.713      1.000    0.832      0.821    0.973     0.713     BeterQ
               0.852    0.049    0.834      0.852    0.843      0.797    0.958     0.782     GoodQ
               0.977    0.030    0.879      0.977    0.925      0.910    0.985     0.878     FairQ
               0.551    0.029    0.832      0.551    0.663      0.616    0.795     0.675     PoorQ
               0.858    0.050    0.866      0.858    0.862      0.811    0.947     0.868     BadQ
Weighted Avg.  0.831    0.042    0.836      0.831    0.825      0.786    0.928     0.793

=== Confusion Matrix ===

   a   b   c   d   e   <-- classified as
 340   0   0   0   0 |   a = BeterQ
  91 546   0   0   4 |   b = GoodQ
   0   0 508  12   0 |   c = FairQ
  46  61  60 328 100 |   d = PoorQ
   0  48  10  54 675 |   e = BadQ
```

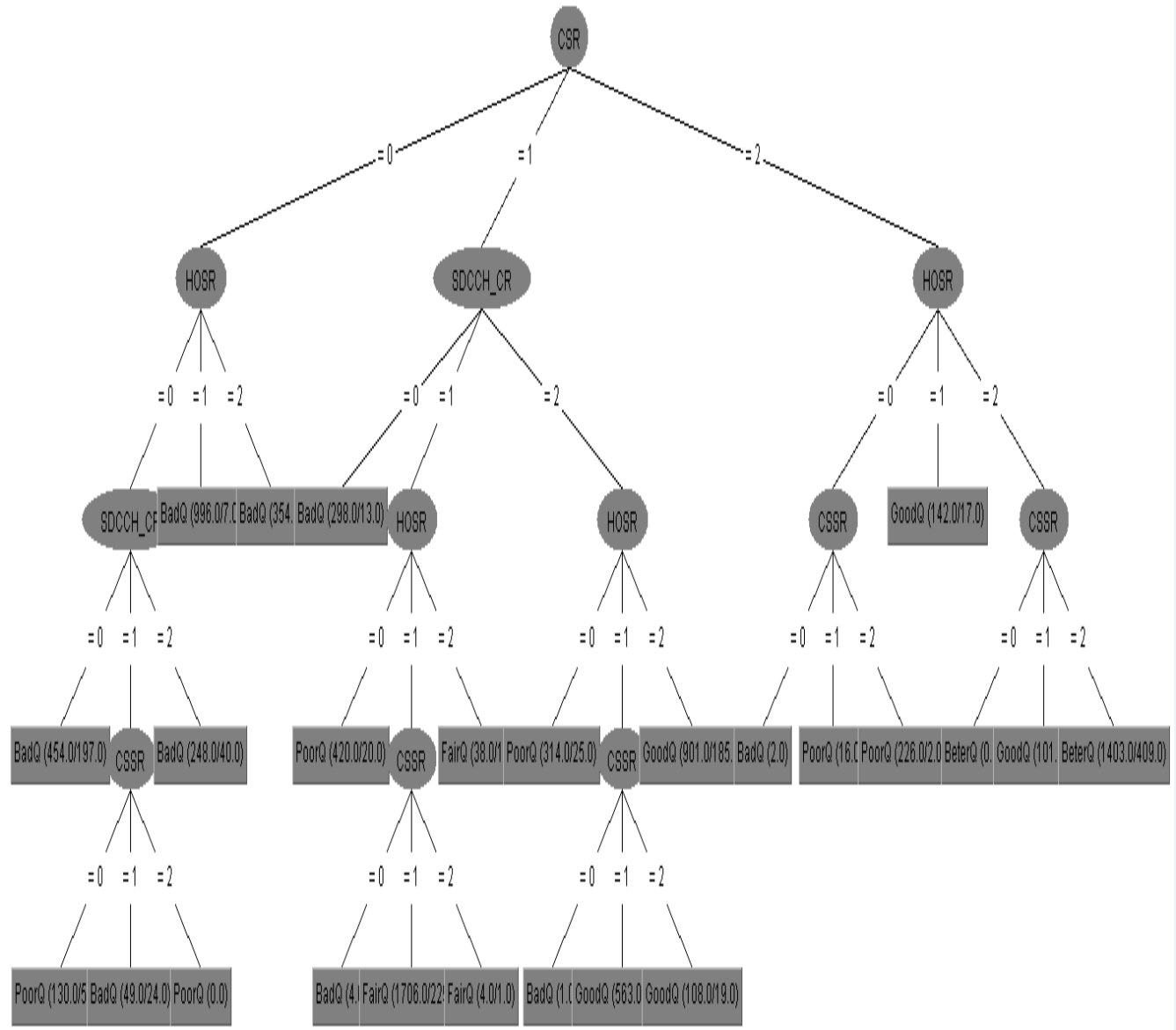
Appendix 4: Summary of results for the selected MLP model

```
=== Summary ===

Correctly Classified Instances        2434               84.4259 %
Incorrectly Classified Instances       449               15.5741 %
Kappa statistic                          0.8033
Mean absolute error                      0.0993
Root mean squared error                  0.2203
Relative absolute error                 31.5714 %
Root relative squared error             55.4911 %
Coverage of cases (0.95 level)          98.6126 %
Mean rel. region size (0.95 level)      39.5491 %
Total Number of Instances             2883

=== Detailed Accuracy By Class ===

               TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
               1.000    0.054    0.713      1.000    0.832      0.821    0.973     0.713     BeterQ
               0.852    0.049    0.834      0.852    0.843      0.797    0.959     0.795     GoodQ
               1.000    0.031    0.877      1.000    0.934      0.922    0.985     0.879     FairQ
               0.563    0.016    0.903      0.563    0.694      0.661    0.883     0.765     PoorQ
               0.881    0.045    0.881      0.881    0.881      0.836    0.966     0.943     BadQ
Weighted Avg.  0.844    0.038    0.854      0.844    0.838      0.805    0.952     0.834

=== Confusion Matrix ===

   a   b   c   d   e   <-- classified as
 340   0   0   0   0 |   a = BeterQ
  91 546   0   0   4 |   b = GoodQ
   0   0 520   0   0 |   c = FairQ
  46  61  63 335  90 |   d = PoorQ
   0  48  10  36 693 |   e = BadQ
```

Appendix 5: The selected MLP classification model network diagram



Appendix 6: The selected J48 Decision tree classifier tree



Appendix 7: Detailed predictive accuracy of the selected J48 model

```
=== Summary ===

Correctly Classified Instances        3567               84.1274 %
Incorrectly Classified Instances       673               15.8726 %
Kappa statistic                          0.7782
Mean absolute error                      0.095
Root mean squared error                  0.2224
Coverage of cases (0.95 level)          97.783  %
Total Number of Instances             4240

=== Detailed Accuracy By Class ===

               TP Rate   FP Rate   Precision   Recall  F-Measure  MCC      ROC Area  PRC Area  Class
               1.000    0.009    0.466      1.000    0.636      0.679    0.995     0.466     BeterQ
               0.971    0.104    0.855      0.971    0.909      0.851    0.949     0.861     GoodQ
               0.989    0.022    0.844      0.989    0.911      0.903    0.990     0.857     FairQ
               0.564    0.017    0.929      0.564    0.702      0.655    0.864     0.778     PoorQ
               0.887    0.069    0.783      0.887    0.832      0.783    0.951     0.881     BadQ
Weighted Avg.  0.841    0.062    0.855      0.841    0.832      0.785    0.930     0.839

=== Confusion Matrix ===

    a    b    c    d    e   <-- classified as
   34    0    0    0    0 |    a = BeterQ
   30 1587    0    0   18 |    b = GoodQ
    0    5  454    0    0 |    c = FairQ
    9  226   69  667  211 |    d = PoorQ
    0   39   15   51  825 |    e = BadQ
```

Appendix 8: Detailed predictive accuracy of the selected Naïve Bayes model

```
=== Summary ===

Correctly Classified Instances        3525               83.1368 %
Incorrectly Classified Instances       715               16.8632 %
Kappa statistic                          0.7634
Mean absolute error                      0.0967
Root mean squared error                  0.2364
Coverage of cases (0.95 level)          94.6934 %
Total Number of Instances             4240

=== Detailed Accuracy By Class ===

               TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
               1.000    0.009    0.466      1.000    0.636      0.679    0.995     0.466     BeterQ
               0.971    0.102    0.857      0.971    0.910      0.853    0.943     0.842     GoodQ
               0.889    0.018    0.859      0.889    0.874      0.858    0.986     0.852     FairQ
               0.581    0.040    0.848      0.581    0.690      0.617    0.804     0.725     PoorQ
               0.870    0.067    0.785      0.870    0.826      0.775    0.932     0.837     BadQ
Weighted Avg.  0.831    0.067    0.836      0.831    0.824      0.769    0.907     0.806

=== Confusion Matrix ===

    a    b    c    d    e   <-- classified as
   34    0    0    0    0 |    a = BeterQ
   30 1587    0    0   18 |    b = GoodQ
    0    0  408   51    0 |    c = FairQ
    9  226   57  687  203 |    d = PoorQ
    0   39   10   72  809 |    e = BadQ
```

Appendix 9: Detailed predictive accuracy of the selected MLP model

```
=== Summary ===

Correctly Classified Instances        3567               84.1274 %
Incorrectly Classified Instances       673               15.8726 %
Kappa statistic                          0.7785
Mean absolute error                      0.0969
Root mean squared error                  0.2228
Coverage of cases (0.95 level)          99.5283 %
Total Number of Instances             4240

=== Detailed Accuracy By Class ===

               TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
               1.000    0.009    0.466      1.000    0.636      0.679    0.995     0.466     BeterQ
               0.971    0.102    0.857      0.971    0.910      0.853    0.951     0.866     GoodQ
               1.000    0.022    0.845      1.000    0.916      0.909    0.990     0.857     FairQ
               0.536    0.008    0.965      0.536    0.690      0.655    0.868     0.787     PoorQ
               0.917    0.079    0.765      0.917    0.834      0.788    0.947     0.895     BadQ
Weighted Avg.  0.841    0.061    0.862      0.841    0.830      0.788    0.931     0.846

=== Confusion Matrix ===

    a    b    c    d    e   <-- classified as
   34    0    0    0    0 |    a = BeterQ
   30 1587    0    0   18 |    b = GoodQ
    0    0  459    0    0 |    c = FairQ
    9  226   69  634  244 |    d = PoorQ
    0   39   15   23  853 |    e = BadQ
```

DECLARATION

I declare that the thesis is my original work and has not been presented for a degree in any other university.

---------- ----------

Signature Date

This thesis has been submitted for examination with my approval as university advisor.

Ato Getachew Jemaneh