ADDIS ABABA UNIVERSITY

ADDIS ABABA INSTITUTE OF TECHNOLOGY

SCHOOL OF ELECTRICAL AND COMPUTER ENGINEERING

UMTS Traffic Model Using Artificial Neural Network: The Case of Addis Ababa, Ethiopia

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Declaration

I declare that this thesis was composed by myself, that the work contained herein is my own except where explicitly stated otherwise in the text, and that this work has not been submitted for any other degree or professional qualification.

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Place: Addis Ababa

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ABSTRACT

Universal Mobile Telecommunications System (UMTS) with wide-band code division multiple access technology (WCDMA) is a major mobile communication system deployed in Ethiopia. WCDMA is being widely deployed in urban areas of the country. Along its deployment and expansion, it is necessary to develop and maintain a good quality of service (QoS) for mobile subscribers. To realize a certain network QoS, one of the prior works to be done is proper capacity planning before deployment. A discrepancy between the installed capacity of an operator and capacity demand of its customers results in inefficiency, either in under-utilized resources or unsatisfied customer. Improper capacity planning can lead to high capital cost or loss of revenue due to unsuccessful calls and low data rate (speed). So, working on capacity analysis needs prudent decisions.

As a network provider, when considering deployment of new networks or expansion of existing networks, knowing the required capacity is a core part of the overall planning process. Typically, forecasted traffic parameters play a major role in determining the user traffic model and dimensioning the total number of users in a cell. Capacity demand may vary based on input parameters, such as busy hour traffic per user, downlink and uplink ratio, and busy hour traffic ratio.

The goal of this thesis is forecast required voice and data capacity of ethio telecom UMTS network using artificial neural network (ANN) model. The forecasting result could be used to minimize discrepancy during planning. Taking Addis Ababa city as a research focus area, real time UMTS traffic measurements were obtained for a period of 14 consecutive months from the Performance Reporting System (PRS). Traffic model forecasting is done by using ANN model. Real time traffic measurement counters are obtained based on the actual voice call traffic and total throughput of data service traffic values. The variation of each input assumption is analyzed with reference to the deployed capacity planning result. The variation due to each input assumption is analyzed with UMTS traffic model cell load analyzer tool which is developed for this study.

Using the operator forecasted total number of subscribers' result data, the result of this study shows that the holding capacity of the network will get efficient if the number of cells remain the same as of the deployed result for the next five years.

Key Words: UMTS; Traffic model; Capacity Planning; Artificial Neural Network model.

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LIST OF ACRONYMS

2G	Second generation
3G	Third generation
3GPP	3rd Generation Partnership Project
AF	Active factor
ANN	Artificial Neural Network
ATM	Asynchronous Transfer Mode
AuC	Authentication Center
BHCA	Busy Hour Call Attempts
BSC	base Station Controller
CS	Circuit Switch
EA	The rate at which the error changes as the activity level of a unit is changed
EI	The rate at which the error changes as the total input received by a unit is changed
EIR	Equipment Identity Register
EW	Error derivative of the Weights
FDD	Frequency Division Duplex
FDMA	frequency division multiple access
GGSN	Gateway GPRS support node
GMSC	Gateway MSC
GPRS	General Packet Radio System
GSM	Global System of Mobile Communication
HLR	Home Location Register
HSPA	High Speed Packet Access
ITU	International Telecommunication Union

MSC	Mobile services switching center
OSS	Operations Support System
PRS	Performance Reporting System
PS	Packet Switch
QoS	Quality of Service
RAN	Radio Access Network
RNC	Radio Network Controller
RNS	Radio Network Systems
SGSN	Serving GPRS support node
TDD	Time Division Duplex
TDMA	Time Division Multiple Access
UMTS	Universal Mobile Telecommunication System
UTRAN	UMTS Terrestrial Radio Access Network
VLR	Visitor Location Register
WCDMA	Wideband Code Division Multiple Access

1. INTRODUCTION

1.1 OVERVIEW

Second generation (2G) systems have enabled voice communications to become wireless the telecom market. But due to their limitations in data handling capabilities and increasing customer's interest in advanced services, third generation (3G) systems are developed to provide the high bit rate services that enable high quality images and video to be transmitted and received, and to provide access to the web with higher data rates.

Universal Mobile Telecommunication System (UMTS) is one of the most important and popular standards of the 3G mobile communication system specified by the 3rd Generation Partnership Project (3GPP). UMTS is designed for flexible delivery of service and radio solution brings advanced capabilities that enable services with high data rate [1]. Each service has its own particular traffic characteristics and specific Quality of Service (QoS) requirements to be met by the network. Over the past few years UMTS has experienced an unprecedented development [2].

At present, the number of UMTS subscribers and operator networks are still growing rapidly. In Ethiopia, ethio telecom widely deployed UMTS in all main towns of the country. As the number of wireless subscribers of UMTS in Ethiopia increases, the demand for good QoS will become a concern for the operator and wireless mobile service users in the country. An important element to improve QoS in UMTS networks is efficient design of the network infrastructure, in particular the radio access network, referred to as UMTS Terrestrial Radio Access Network (UTRAN). The radio access network bandwidth bottleneck in the wireless media is considered as one of the most important economic factor for network dimensioning because weak and poor service delivery decrease the business expectations of the operator. As the number of mobile users and traffic volume is rapidly growing, it will have negative impact on the system if the network infrastructure capacity is not ready to accommodate. To achieve a good QoS in the UMTS networks, the radio access networks have to be dimensioned suitably for all types of offered services.

For an accurate dimensioning work, proper user traffic model that is used to estimate customers' traffic behavior is highly required. Hence, this thesis presents optimized new user traffic model that can be used to enhance the mathematical analysis of the capacity planning result and network element dimensioning. The analysis will provide the total number of users that can be supported in a single cell/carrier. So, with a properly dimensioned UMTS radio access network, we can increase the service quality offered to users.

1.2 STATEMENT OF THE PROBLEM

Ethio telecom is providing 3G/UMTS service to its clients in Addis Ababa and urban areas across the country. In UMTS network planning, capacity planning is done based on the operator's input traffic parameters. Different operators use different assumption value in traffic parameters. The traffic models will lead the capacity and dimensioning result to vary among operators.

User traffic parameters used in capacity planning mathematical calculation determine the accuracy of total traffic load, number of customers that will be served per unit cell, and quality of the network. In capacity planning, excessive over-dimensioning waste the expensive bandwidth resources unnecessarily while under-dimensioning can lead to a less satisfactory QoS perceived by the mobile users.

Enhancing the accuracy of the traffic model, the voice and data traffic parameters of users, by studying and using history traffic data is the core reason of this thesis work. User traffic parameter determination at peak hour for capacity planning calculation is the main focus. To increase quality of service in the wireless communication, inputs used in the user traffic parameters, values that determine the mathematical planning and dimensioning result, will give a better dimensioning result if they are taken by studying their past history data rather than using theoretical assumption values only.

This work takes an initiation to predict UMTS traffic model from the real time traffic measurement. Single user traffic usage is forecasted so as to give the operator's (ethio telecom) peak (busy) hour user traffic data that will be used in capacity planning and helps the operator in dimensioning the network element ahead of time (for new and future expansion projects). This help the operator in minimizing traffic congestion and improving quality of service that will maximize company revenue.

1.3 THESIS OBJECTIVE

General objective

The core objective of this research is to forecast UMTS traffic model using artificial neural network. The forecasted traffic model could be used in UMTS capacity planning analysis. From the measured history traffic data, Addis Ababa users' traffic parameters will be predicted using ANN.

Specific objectives

This study is carried out specifically:

- ✓ To customize a mathematical model with Artificial Neural Network that used for forecasting.
- ✓ To determine the operators' peak (busy) hour user traffic ahead of time.
- ✓ To develop analyzer tool with Microsoft visual basic that used to observe the variation in capacity analysis result due to the input user traffic usage parameters.
- ✓ To analyze the real time traffic measurement of Addis Ababa using deployed traffic model as a reference.
- ✓ To determine busy hour traffic ratio, total downlink, and uplink traffic usage ratio and per user voice traffic values for the individual user traffic profile which are the input assumptions in the capacity planning.
- ✓ To predict future traffic model using ANN.

1.4 LITERATURE REVIEW

Several researchers have been and are working to develop computational methods which are based on how biological nerve system and brain are working. Neuron based chips are evolving and applications to complex problems are also developing. Besides neuroscience, psychologists and engineers also contributed to the progress of neural network and neural network simulations. Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. A trained neural network can be thought as an "expert" in the category of information it has been given to analyze [3].

Neural networks offer a better alternative approach to computing and provide a different approach to problem solving than the conventional computers. Conventional computer follows a set of instructions to solve a problem. There are tasks that are more suitable to an algorithmic approach like arithmetic operations. Neural networks offer the opportunity to solve problems in an arena where traditional processors lack both the processing power and a step-by-step methodology. This new way of computing requires skills beyond traditional computing. This skill of making neural networks work is one that will stress the logical thinking of current software engineers. Clearly, today is a period of transition for neural network technology.

The reviewed literatures of this thesis work are journals, conference papers and thesis works which use artificial neural network as a forecasting model in their prediction. Some of the reviewed works are described below.

Oladeji E.O, et al. established the traffic pattern over 24 hours in Nigeria for a period of 5 months using an operator switch in the north-central part of Nigeria with 6 Base Station Controllers (BSC) [4]. The busy hour is determined and a model for traffic forecasting is also developed. The data obtained from Network Management System (NMS) counter for a period of 5 months was analyzed using ANN and they determined the busy hour where it predominantly occurs. Core observation point from [4] is that ANN can give a better prediction as long as correct data are supplied.

Chao Xi et al. used ANN for weather forecast through the historical database which implemented in the local weather station. Back Propagation algorithm using gradient descent method algorithm is used to train a neural network. Prediction has tied by giving history data using back propagation algorithm with ANN in [5]. Observation from [5] can be seen that using back propagation algorithm in ANN, past values can be used to predict future time steps as long as enough history data is given as an input to ANN. Back propagation will be discussed in chapter 4.

Estimation of the total vehicular delay according to the lane type at a toll plaza to avoid the laborious task of extracting data from the video recordings at a toll plaza is carried using the application of ANN in [6]. Observation from [6] is that ANN can be used as an estimation application by providing necessary history data.

Dong Ling Zhang, et al. in [7] used Hidden Markov Models (HMM) to forecast busy hour traffic of wireless mobile communication. The study in [7] gives a core point that busy hour traffic data can be predicted in a model from their past traffic user characteristics.

J.-S. Yang, et al. in [8] used Multi-step-ahead predictor design for effective long-term forecast of hydrological signals using a novel wavelet neural network hybrid model. Observation from [8] is that multi-step ahead prediction can be carried and user traffic profiles on UMTS network can be predicted as long as history data is given as an input to ANN.

Fi-john Chang, et al. in [9] used multi-step ahead neural networks for flood forecasting, that will help to reliable flood warning system. Multi-step values are predicted ahead of time using their past measurement. So, from [9] observation can be taken that multi-step forecasting values can be obtained using a trained model that can be used to predict future values based on its past values input.

1.5 METHODOLOGY

The methodology used in the thesis mainly constitute a frame work based on mathematical model development, analyzer tool design and result interpretation.

In mathematical model development, ANN is applied to forecast UMTS/WCDMA user traffic model. ANN forecasting model process is as follows.

- ✓ Data from performance reporting system is combined in excel.

- ✓ Artificial neural network (ANN) analyzer model is customized in MATLAB.
- ✓ ANN model training.
- ✓ Forecasting with the trained model.

Real time measurements and forecasted user traffic parameters are analyzed with a new UMTS traffic model Cell load analyzer tool developed for this study with Microsoft visual basic.

Data interpretation is done based on the results obtained from the forecasting ANN model and Cell load analyzer tool.

1.6 SCOPE AND LIMITATION OF THE THESIS

The scope of this study is to predict user traffic parameters which are input assumptions in capacity planning based on real time measurement data forecasted results.

- ✓ This study covers only UMTS capacity planning, it will not give details to 2G GSM as well 4G LTE systems.
- ✓ The real time measurement data is obtained from the performance monitoring tool of the operator. So, the user traffic forecasted results that are used to determine the traffic profile of users are limited to traffic measurements values which are available in the performance measurement database system.
- ✓ From the collected real time performance data, forecasting will be done with ANN model and a new per user traffic parameters will be determined ahead of time.
- ✓ The input assumptions, which are user traffic usage parameters used in capacity planning and the main focus of this thesis work, used in the forecasting process are :

1. Traffic per user
2. Busy Hour total downlink and uplink traffic ratio and
3. Busy Hour traffic ratio.

- ✓ Since Addis Ababa UMTS user traffic is the main focus of this study, the measurements collected from the performance system is bonded to Addis Ababa network, which limit the scope to focus on Addis Ababa.

Limitations

- ✓ Total number of forecasted subscriber (customer) and active subscriber ratio value are directly taken from the operator forecasting result. In UMTS capacity analysis, total number of customers will play a key role in the mathematical calculations and findings. So, the new user traffic profile result of this study is based on the company assumption result that may increase or decrease from the exact number of the total customer number.
- ✓ In this thesis, it is assumed that the business plan will not have radical price change that will vary the traffic abruptly.
- ✓ To consider seasonal influences of traffic and aggregate a cumulative effect, a long period data was preferable. But in this study, only one year history data is the maximum data that can be obtained from the system.
- ✓ The new forecasted traffic model of this thesis, that used to determine the peak time cell load result, is obtained based on traffic measurement which is available in the Performance Reporting System.

1.7 CONTRIBUTION

In capacity planning, user traffic parameter values can lead the result to overestimated or under estimated dimensioning result. Either results will affect to achieve the planned target quality. Findings from this thesis will contribute to increase the accuracy of capacity planning. Operator defined traffic model values will be supported with system measurement past (history) traffic values. Real time traffic measurements can tell more about user traffic parameters. Measurement-based new user traffic forecasted values result from this thesis work will contribute by providing UMTS user traffic parameters which enhance and maximize the capacity analysis result by estimating accurately the required number of wireless access network elements. It will be also used to combine and compare operator defined user traffic values with real time measurement results in new and expansion project capacity analysis work.

1.8 THESIS OUTLINE

This thesis provides a detailed description on how ANN is used for capacity planning based on UMTS user traffic measurements. Chapter 2 presents the 3G network, UMTS, and the details of UMTS traffic. Chapter 3 introduces the principles of the capacity planning. It includes parameters used in the capacity planning calculation, such as busy hour traffic, downlink and uplink traffic ratio and busy hour traffic ratio. Chapter 4 gives a presentation about the forecasting model and Artificial Neural Network (ANN). Chapter 5 presents results and discussion. Finally, Chapter 6 concludes this thesis work and gives some directions for future work.

2. UMTS AND UMTS TRAFFIC

2.1 UNIVERSAL MOBILE TELECOMMUNICATION SYSTEM

The UMTS is a 3G mobile communications system that provides a range of broadband services to the world of wireless and mobile communication users. It is a widely adopted 3G wireless cellular standard. Wide-band CDMA (WCDMA) is the air interface for UMTS [10][11]. WCDMA is based on CDMA for transmission, which is its defining characteristic. It was designed to advance 2G cellular standards and enable the transmission of high quality images and video over wireless connections with the aim of enabling IP-based broadband services [10]. Broadband and packet-based transmission of text, digitized voice, video, and multimedia at data rates up to and possibly higher than 2 megabits per second (Mbps) offering with a consistent set of services to mobile computer and phone. UMTS efforts were initiated in the 1992 meeting of the International Telecommunication Union (ITU). Its original goal was to design a single 3rd generation air interface. Commercial networks were first deployed in early 2001 in Japan and later rolled out in Europe in 2002 [11].

2.2 UMTS ARCHITECTURE

UMTS architecture consists of two main parts; core network and UMTS terrestrial radio access network (UTRAN).

2.2.1 CORE NETWORK

The UMTS core network is based on the Global System of Mobile Communication (GSM)/General Packet Radio System (GPRS) network topology. Core network provides switching, routing, transport, and database functions for user traffic. The core network contains circuit-switched elements such as the Mobile Services Switching center (MSC), visitor location register (VLR), and gateway MSC (GMSC). It also contains the packet-switched elements Serving GPRS support node (SGSN) and gateway GPRS support node (GGSN). The equipment identity register (EIR), home location register (HLR), and authentication center (AuC) support both circuit and packet switched data [12][13][14]. The UMTS architecture is shown in Figure 2.1.

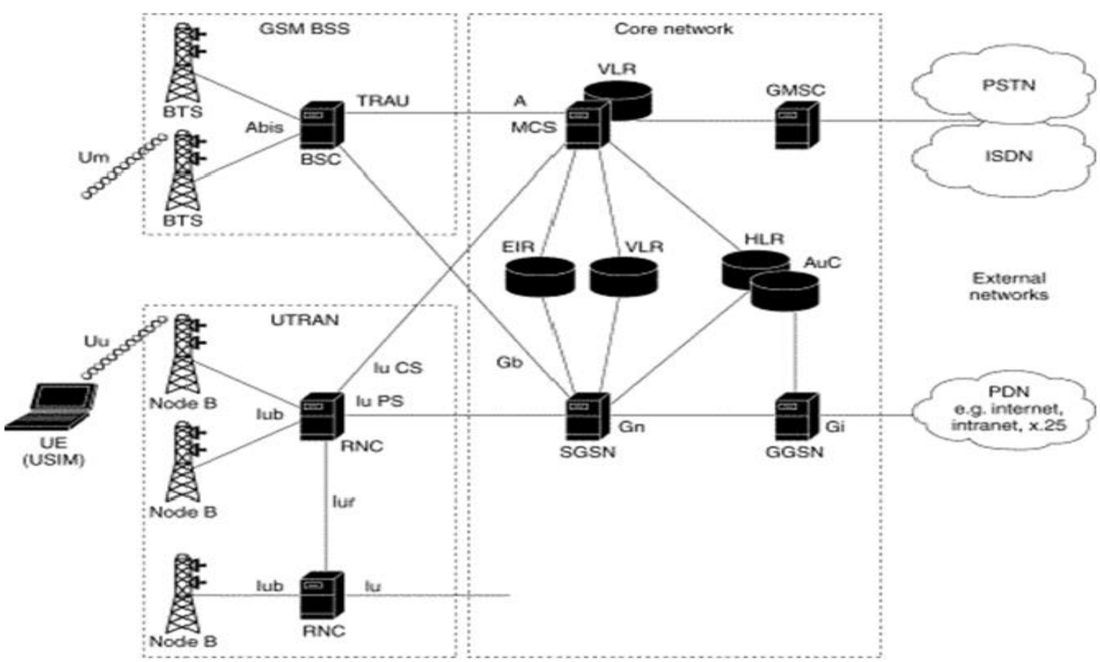

Figure 2-1 UMTS Architecture [15].

2.2.2 UMTS TERRESTRIAL RADIO ACCESS NETWORK

The major difference between GSM/GPRS and UMTS networks is in the air interface transmission. Time division multiple access (TDMA) and frequency division multiple access (FDMA) are used in GSM/GPRS networks. The air interface access method for UMTS networks is wide-band code division multiple access (WCDMA), which has two basic modes of operation: frequency division duplex (FDD) and time division duplex (TDD). These new air interface access methods require a new radio access network (RAN) called the UMTS terrestrial RAN (UTRAN). The 2G core network requires minor modifications to accommodate the UTRAN [16].

Two new network elements are introduced in the UTRAN: the radio network controller (RNC) and Node B. The UTRAN contains multiple radio network systems (RNSs) and each RNS is controlled by an RNC. The RNC connects to one or more Node B elements. Each Node B can provide service to multiple cells [15].

The RNC in UMTS networks provides functions equivalent to the base station controller (BSC) functions in GSM/GPRS networks. Node B in UMTS networks is equivalent to the base transceiver station (BTS) in GSM/GPRS networks. In GSM/GPRS networks, radio resource management is performed in the core network. In UMTS networks, this function is distributed to the RNC, freeing the core network for other functions.

A single serving RNC manages serving control functions such as connection to the UE, congestion control, and handover procedures. The functions of the RNC include radio resource control, admission control, channel allocation, power control settings, handover control, macro diversity, ciphering, segmentation and reassembly, broadcast signaling and open loop power control. It enables new services over existing interfaces (such as *A*, *Gb*, and *Abis*) and new interfaces that include the UTRAN interface between Node B and the RNC (*Iub*) and the UTRAN interface between two RNCs (*Iur*) [15]. The RNC provides centralized operation and maintenance of the radio network system (RNS) including access to an operations support system (OSS).

Node B is the radio transmission/reception unit for communication between radio cells. Each Node B unit can provide service for one or more cells. A Node B unit can be physically located with an existing GSM base transceiver station (BTS) to reduce costs of UMTS implementation. Node B connects to the user equipment (UE) over the *Uu* radio interface using wide-band code division multiple access (WCDMA).

A single Node B unit can support both frequency division duplex (FDD) and time division duplex (TDD) modes. The *Iub* interface provides the connection between Node B and the RNC using asynchronous transfer mode (ATM). Node B is the ATM termination point [15][17][18].

The UMTS user equipment (UE) is the combination of the subscriber's mobile equipment and the UMTS subscriber identity module (USIM). Similar to the SIM in GSM/GPRS networks, the USIM is a card that inserts into the mobile equipment and identifies the subscriber to the core network. The USIM card has the same physical characteristics as the GSM/GPRS SIM card and provides the following functions, Supports multiple user profiles on the USIM, Updates USIM information over the air, Provides security functions, Provides user authentication, Supports inclusion of payment methods and Supports secure downloading of new applications. The UMTS standard places no restrictions on the functions that the UE can provide. Many of the identity types for UE devices are taken directly from GSM specifications [15].

2.3 UMTS HSPA

3G High Speed packet Access (HSPA) is the combination of two technologies, one for the downlink and the other for the uplink that can be built onto the existing 3G UMTS or WCDMA technology to provide increased data transfer speed [19]. The original 3G UMTS/W-CDMA standard provided a maximum download speed of 384 kbps. With many users requiring much high data transfer speeds to compete with fixed line broadband services and also to support services that require higher data rates, the need for an increase in the speed obtainable became necessary. This resulted in the development of the technologies for 3G HSPA. HSPA provides a number of significant benefits that enable the new service to provide a far better performance for the user. High Speed Packet data is an upgrade to both FDD and TDD. The upgrade and introduction was done in steps; High Speed Down Link (DL) Packet data Access (HSDPA), was introduced in 3GPP Release 5, and Enhanced Up Link (UL), also referred to as High Speed Uplink (UL) Packet data Access (HSUPA), came in Release 6 [20]. 3GPP releases and their features are shown in the below table.

Table 2-1 HSPA features [21].

3G HSPA SPEED & SALIENT FEATURES			
3GPP RELEASE	**TECHNOLOGY**	**DOWNLINK SPEED (MBPS)**	**UPLINK SPEED (MBPS)**
Release 5	HSDPA	14.4	0.384
Release 6	HSUPA	14.4	5.7

Release 7	2X2 MIMO, DL 16 QAM, UL 16 QAM, 5/5 MHz	28	11
Release 8	2X2 MIMO DL 64 QAM, UL 16 QAM, 5/5 MHz	42	11
Release 8	(no MIMO) Dual Carrier, 10/5 MHz	42	11
Release 9	2X2 MIMO DL, DL 64 QAM, UL 16 QAM, Dual Carrier, 10/10 MHz	84	23
Release 10	2X2 MIMO DL, DL 64 QAM, UL 16 QAM, Quad Carrier, 20/10 MHz	168	23
Release 11	2X2 MIMO DL and UL, DL 64 QAM, UL 16 QAM, Quad Carrier, 40/10 MHz	336	70

2.4 UMTS TRAFFIC

UMTS/WCDMA system provides the users with flexible and diversified services, which is an important characteristic of WCDMA. The WCDMA system supports multiple services:

- ✓ Variable-rate services (e.g. Adaptive multi rate (AMR) voice)

- ✓ Combined services (e.g. Circuit Switch (CS) and Packet Switch (PS))
- ✓ High-speed data packet services
- ✓ Asymmetrical services (e.g. stream service)
- ✓ Large-capacity and flexible service bearing

In different propagation environment, the WCDMA system requires reaching different target transmission rate values, e.g., in high-speed motion, the rate is up to 144 Kbps; in case of walking, the rate is up to 384 Kbps, and the rate in indoor environments is up to 2 Mbps. WCDMA considers the future service development requirements, and provides sufficient capacity and data bearing capability of flexible rate matching methods.

The QoS of the WCDMA service is described by data rate, bit error rate (BER), transmission delay, and delay jitters. Different services and service composition proportions affect the WCDMA performance significantly. Therefore, the WCDMA network planning analysis should be based on the prerequisite of a certain traffic model estimate.

2.4.1 TRAFFIC MODEL

Traffic model is a means to investigate the capacity features of each service type and the QoS expected by the users who are using the service from perspective of data transmission. In the data application, the user behavior research mainly forecasts the service types available from the 3G, the number of users of each service type, frequency of using the service, and the distribution of users in different regions [22].

Setting up traffic model has the following objectives.

- ✓ In order to determine the system configuration, we need to determine the capacity of the air interface first.

- ✓ In the data service, different transmission model will generate different system capacities.
- ✓ We need to set up an expected data transmission model of the customer so that we can plan the network properly.

In order to set up a right model, the operators should provide some performance data as reference. The system has many key performance indicators, e.g., coverage, spectrum efficiency, and capacity, which are closely related to the type of service carried by the system. Therefore, in order to predict the performance of the WCDMA system in carrying a certain type of service, the service features must be known. Service features are represented by the traffic model.

2.4.1.1 Contents of a traffic model

The contents of a traffic model are service patterns and user behaviors. Service pattern refers to the service features and user behavior refers to the conduct of people in using the service. In the actual application service pattern is closely related to, and sometimes is no strictly different from, the traffic measurement model. By determining the service pattern and the user behavior parameters, we determine the traffic models of various services in the network. By calculating the hybrid services of multiple traffic models, we determine the network system configuration. In this study these two features are analyzed based on the collected real time history data and from theoretical point of views. The patterns and some user's behavior descriptions are presented in Chapter 5.

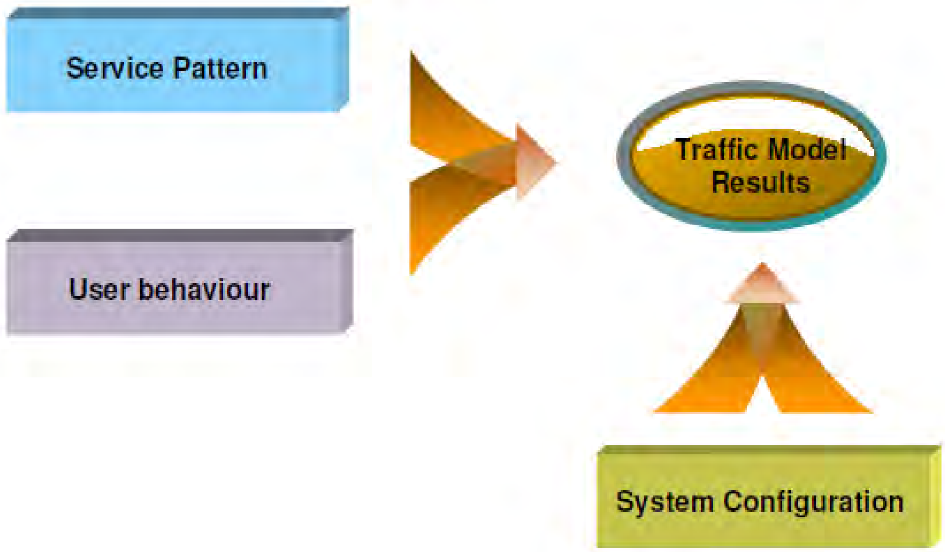

Figure 2-2 The contents of the traffic model [22].

2.4.1.2 QoS requirements of the service

For each service, since the channel structure and demodulation method are different, the required uplink rate is different from the required downlink rate even for the same service type and the same data rate. For a typical service, first we need to identify whether it is uplink or downlink rate is required. A typical service can be described by the following parameters [22]:

- ✓ User type (indoor users, users inside a vehicle, outdoor users)
- ✓ User's average moving speed (km/h)
- ✓ Voice, real-time data, non-real time data
- ✓ Uplink and downlink service rates (kbps)
- ✓ Spread factor (SF)
- ✓ Signal delay requirement of the service (ms)

The above parameters ultimately determine QoS requirements of the service.

2.4.1.3 Quality of service type

Services can be categorized by real time and non-real time. Real time category includes session (conversational) and streaming service types and non-real time category includes interactive and background services types.

- ✓ Session-type service

Requirement on end-to-end delay is strict. For example, for the voice service, the delay is required to be smaller than 150ms, and must not exceed 400 ms; otherwise, it will be difficult to understand the voice. The session-type services are typically carried by the circuit switched (CS) domain. For the session-type services, the system can perform no queue processing for the calls. Number of trunks or lines are needed to handle the real time call service to avoid lost calls. In addition to lost calls, the assumption that a caller will retry when he gets busy signal will be also considered in the real time voice call system. This kind of real time services will be designed based on Erlang B and Erlang C concepts.

- ✓ Stream-type service

Compared with the session-type service, the stream-type service imposes low requirement on the end-to-end delay. Generally, the stream-type service tolerates the call waiting to a greater extent, and can provide the call queue mechanism. In this case, we can use the Erlang C concept to calculate the blocking probability (defined as the probability of the call waiting for a specified time).

- ✓ Interaction-type service

Refers to the service through which the user requests data from the server. The service is described with the terminal user's request response pattern. Therefore, round-trip delay is the most important index of this service type. The interaction-type services are typically carried on the CS domain.

- ✓ Background-service

The background-service tolerates delay to the greatest extent, and can tolerate the delay of a magnitude of an hour. Due to such great delay tolerance, the system can save such requests in the busy hour and respond when the channel becomes idle; meanwhile, for such services, once a request with higher QoS comes in, the processing can be stopped at any time. The system decides startup and termination at any time. For the background-service type, Erlang B and Erlang C formula are not applicable [22].

Table 2.3 Services and quality of service [22].

Real-time category	Conversational	It is necessary to maintain the time relationship between the information entities in the stream. Small time delay tolerance. Symmetry data rate required.	Voice service, videophone
	Streaming	Unidirectional services, high requirement on error tolerance and high requirement on data rate.	Streaming multimedia
Non real-time category	Interactive	Request-response mode, data integrity must be maintained. High requirement on error tolerance and low requirement on time delay tolerance.	Web page browse, network game
	Background	Data integrity should be maintained. Small delay restriction requires correct transmission.	Background downloads of Email.

2.4.2 CIRCUIT SWITCHED (CS) TRAFFIC MODEL

Voice service is a typical circuit switched services. Voice data arrival conforms to the Poisson distribution. Its time interval conforms to the exponent distribution.

Key parameters of the CS model are:

- ✓ Penetration rate
- ✓ Mean busy-hour call attempts (BHCA)
- ✓ Mean call duration (s)
- ✓ Activation factor
- ✓ Mean rate of service (kbps)

CS Traffic Model Parameters:

For CS service, the busy hour traffic per user in Erlang is calculated as follows [22]:

$$\mathbf{B_A}\ (\text{Erlang}) = \frac{(\boldsymbol{BHCA})(\mathbf{Ct})}{\mathbf{3600}} \tag{2.1}$$

Where

B_A is mean busy-hour traffic per user.

BHCA is busy hour call attempt.

Ct is mean call duration.

The Erlang value in CS domain is converted to data volume (kbps) with the formula:

$$\mathbf{B_V\ (kbps) = BHCA * Ct * Activation\ factor * Rt} \tag{2.2}$$

Where

B_V is mean busy-hour throughput per use.

Ct is mean call duration.

Rt is mean rate of service (kbps).

2.4.3 PACKET SWITCHED (PS) TRAFFIC MODEL

The basic parameters in the PS traffic model are determined in the following ways:

- ✓ Obtain numerous basic parameter sample data from the existing network.
- ✓ Obtain the probability distribution of the parameters through processing of the sample data.
- ✓ Take the distribution most proximate to the standard probability as the corresponding parameter distribution through comparison with the standard distribution function.

The parameter value varies between different services. During planning, according to the actual situation, we select the typical value of the bear rate.

PS User Behavior Parameters

The country, region, life custom and economic level will affect the service distribution. In the planning, the users are divided into high-end users, mid-end users and low-end users. Busy-hour session attempts (BHSA) and penetration rate are different between different types of user groups.

- ✓ Penetration rate

The percentage of the users that activates this service to all the users registered in the network.

- ✓ Busy-hour session attempts (BHSA)

The times of single-user busy hour sessions of this service.

- ✓ User Distribution (High, Medium, Low end)

The users are divided into high-end, mid-end and low-end users. Different operators and different application situations will have different user distributions.

Figure 2.3 User behavior parameters for PS.

PS Traffic Model Parameters

- ✓ Session traffic volume (Byte) : Average traffic of single session of the service

$$\mathbf{Stv} = \frac{\mathbf{Ps}\ (\mathbf{Pn}/\mathbf{Pc})\ \mathbf{Pcn}}{\boldsymbol{S}} \qquad (2.3)$$

Where

Stv is Session Traffic Volume.

Ps is Packet size.

Pn is Packet number.

Pc is Packet call.

Pcn is Packet call number.

S is Session.

- ✓ Data transmission time (s) : the time in a single session of service for purpose of transmitting data.
- ✓ Holding Time (s) : Average duration of a single session of service

- ✓ Active factor (AF): The weight of the time of service full-rate transmission among the duration of a single session.

$$\textbf{Active factor} = \frac{\textbf{Data Transmission Time}}{\textbf{Holding Time}} \quad (2.4)$$

- ✓ Busy hour throughput per user
- ✓ PS throughput equivalent Erlang formula (Erlang)

$$\textbf{Data Erlang} = \sum(\textbf{Pr}\ (\frac{\textbf{BHe}}{\textbf{Rb} * \textbf{3600} * \textbf{Active Factor}}) \quad (2.5)$$

Where

Pr is Percentage of different user penetration rate

BHe is busy hour throughput under typical application environment

Rb is typical bearer rate

The concept of traffic model will lead to capacity analysis. The capacity calculation is based on the operator user traffic profile values. In chapter three, the details of capacity planning and its fundamental equations will be seen.

3. UMTS CAPACITY PLANNING

3.1 OVERVIEW

UMTS capacity planning design has some complication, than its previous technology (GSM). UMTS has been designed to harvest virtually unlimited business expectations. UMTS offers more capacity and supports higher bandwidths than its predecessors. The extended service portfolio includes location-based services, music download and mobile Internet usage [23]. The most crucial part in planning is getting the required information for a network plan. Different information from various sources are needed for initial capacity design. The required design data includes both the operator and customers' service type that the planning forced to fit together. User traffic information on mobile usage is very helpful for a proper capacity planning work. These user traffic profiles are values that will be settled prior to capacity planning by the network operator. But, taking assumptions to set the user traffic profile values is difficult, because a prediction or guess has to be done as to what the UMTS mobile service mix and usage will be. Mobile usage profiles and customer distribution information is required to simulate the network load. This information is used to estimate the number of Node B and helps the operator to ask vendors to guarantee capacity load level, using the minimum amount of base stations and cost.

Generally, there are two main requirements to decide the total number of cells in design time, capacity and coverage. In coverage requirement, the link budget is used to calculate the maximum allowed path loss and the maximum range for cell. The link budget includes the interference margin and the mathematical calculation used to estimate the required base station amount in each network area. In capacity requirement, the planned customers and service usage in each area of the network is used to get the required amount of Node B. In this thesis, by studying the user traffic profile of Addis Ababa city, a capacity analysis will be presented for UMTS network. So, in this Chapter, capacity planning and its detail mathematical calculation will be discussed.

3.2 CAPACITY PLANNING

Capacity planning is a fundamental part of the radio network planning process that denotes the activity to ensure that the currently available resources are used to provide the highest performance to the users. Capacity planning refers to the activity of ensuring that adequate resources will be available to meet the future workload demands while meeting the performance objectives. Capacity of cellular system is of major concern to operators due to its economic value. For any multiuser communication system, the measure of its economic usefulness is not the maximum number of users which can be serviced at one time, but rather the peak load that can be supported with a given quality and with availability of service [24]. In the capacity planning process, how many mobile users each cell can serve will be estimated. This will be done based on number of subscribers and growth estimations, traffic /user/ busy hour / and required throughput including service mixes. Each type of traffic has to be estimated for capacity calculations. Once the cell capacity and subscriber traffic profiles are known, network area base station requirements can be calculated. Capacity estimations can be done in Erlang per subscriber or kilobits per subscriber (or kilobits per second per subscriber) [25].

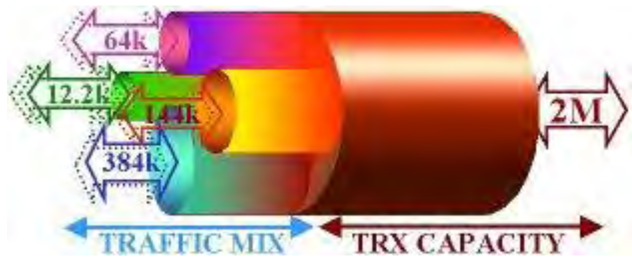

Figure 3-1 Mixed traffic and Capacity [24].

3.3 CAPACITY PLANNING PROCEDURES

UMTS capacity dimensioning procedures are used to obtain the number of subscribers supported per cell. Based on the user traffic usage, coverage and the QoS requirements, Figure 3-2 below shows how operators follows the procedure in dimensioning and capacity planning.

The main steps of capacity dimensioning in the deployed ethio telecom UMTS network are:

a. Obtaining the total number of subscribers from the company forecasted result.
b. According to the user traffic model, total traffic load per connection in CS domain, for voice service, and in PS domain, for data service, will be calculated.
c. Based on simulation done in Vendor Company, the cell load will be obtained.
d. According to load per connection for different service and cell load, the subscribers per cell per different service will be obtained.
e. The minimum, from the different service of subscribers, per cell value will

be taken as the final result.

f. Finally, total site number will be obtained based on the subscriber per cell result. Coverage dimensioning and capacity dimensioning results will be compared and the largest is taken as the final result.

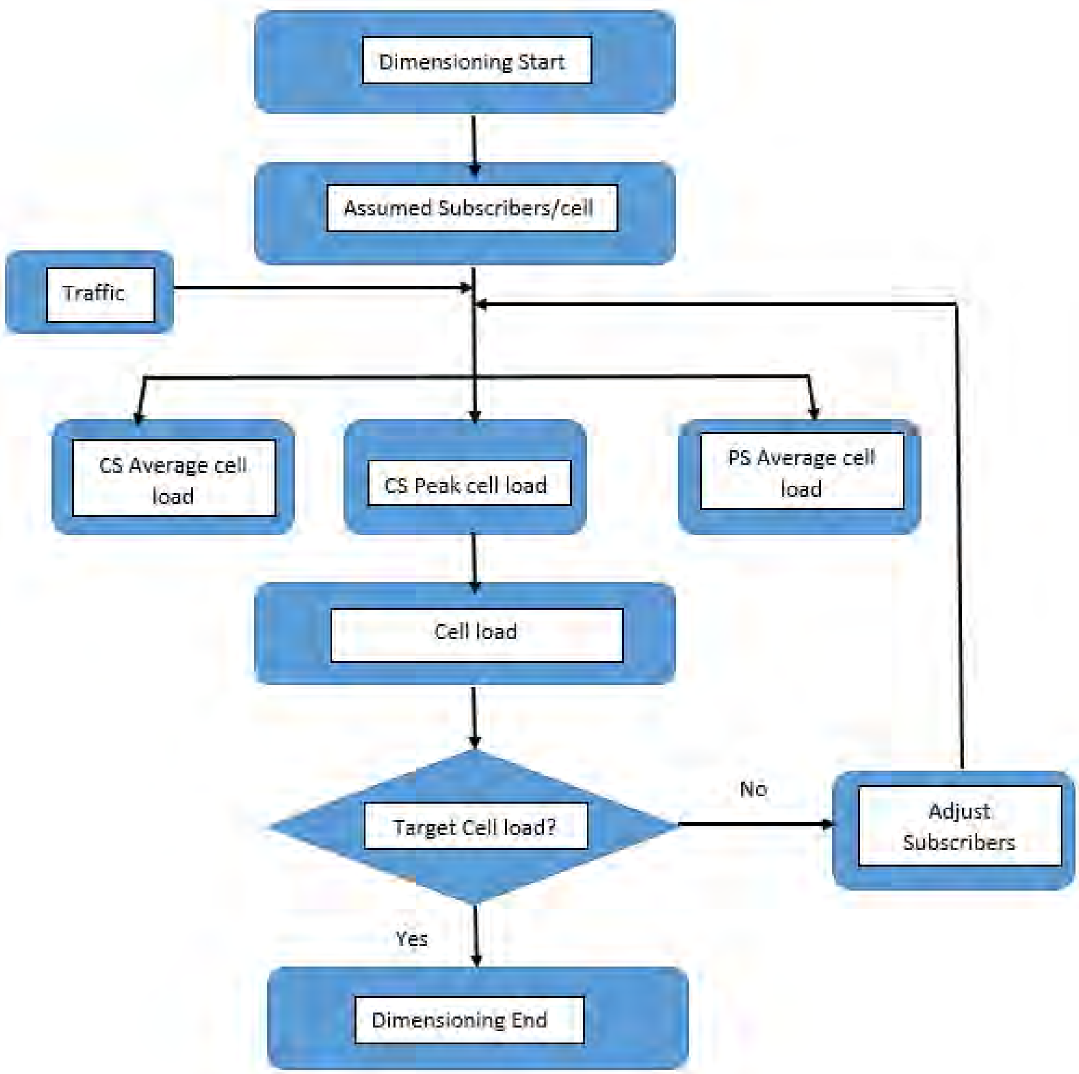

Figure 3-2 UMTS Capacity Dimension Procedure [22].

3.4 PARAMETERS USED IN CAPACITY PLANNING

In the user traffic set values, the input assumption is mainly two types: subscriber number and user usage (user traffic profile).

3.4.1 Subscriber number:

Subscriber number in capacity planning calculation is grouped as,

- ✓ Total subscriber and
- ✓ Active Subscriber

Total subscriber number is the total forecasted UMTS mobile user. Active subscriber is the number of users which can participate during busy hour traffic.

3.4.2 User Traffic Profile

User traffic profiles are user traffic characteristics. In capacity planning, operators are expected to set an appropriate assumption to calculate the cell load result. The main focus of this thesis work user profiles are described below.

3.4.2.1 Busy Hour traffic

The volume of user traffic carried by a cellular network is continuously changing with respect to time. The uninterrupted period of sixty minutes during which the traffic is at a maximum is known as the busy hour [26]. The busy hour can be defined as either fixed or bouncing. The fixed busy hour is a set period of 60 minutes that does not change from day to day. In this type, the user busy hour traffic characteristic is assumed to be uniform with in the fixed set hour in all days of observation. The bouncing busy hour is determined for each day independently. To determine the bouncing busy hour, the network element has to collect traffic data over the entire 24 hours. The bouncing busy hour can be also observed with:

- ✓ Daily variation
- ✓ Weekly variation

- ✓ Week day /weekend variation
- ✓ Seasonal variation.

The amount of traffic experienced during the busy hour is generally used as the basis for traffic calculations and resource dimensioning. In this thesis, the busy hour is determined by collecting traffic data over the entire 24 hours for a period of 14 consecutive months.

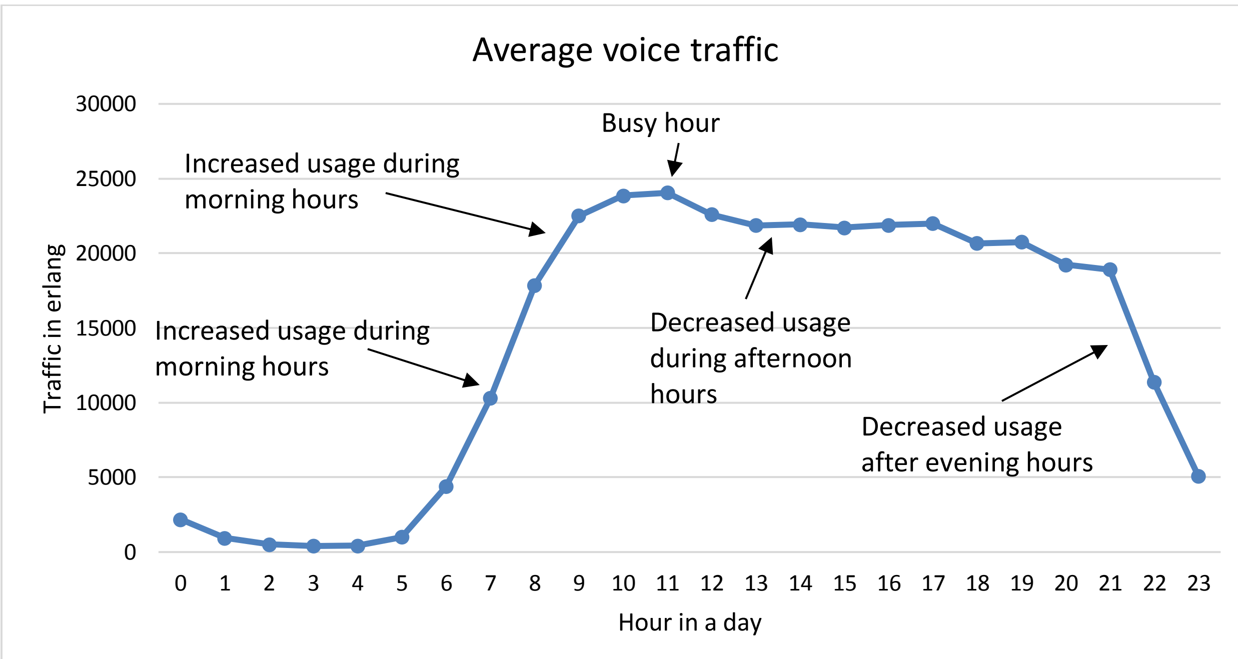

Figure 3-3 CS Average busy hour pattern of May 2016.

As indicated in Figures 3.3 and 3.4, CS and PS domain busy hour traffic are described. Both type of traffic, voice and data, have an increasing trend in the morning time. Voice traffic reaches its peak hour during lunch time at 11: 00. Whereas the PS traffic goes with an increasing rate till evening and reaches its peak hour before midnight at 22:00. Morning around lunch time is the heavy traffic that the network is expected to hold voice traffic and evening before midnight is the time where heavy load from the packet switched domain is loaded to the network.

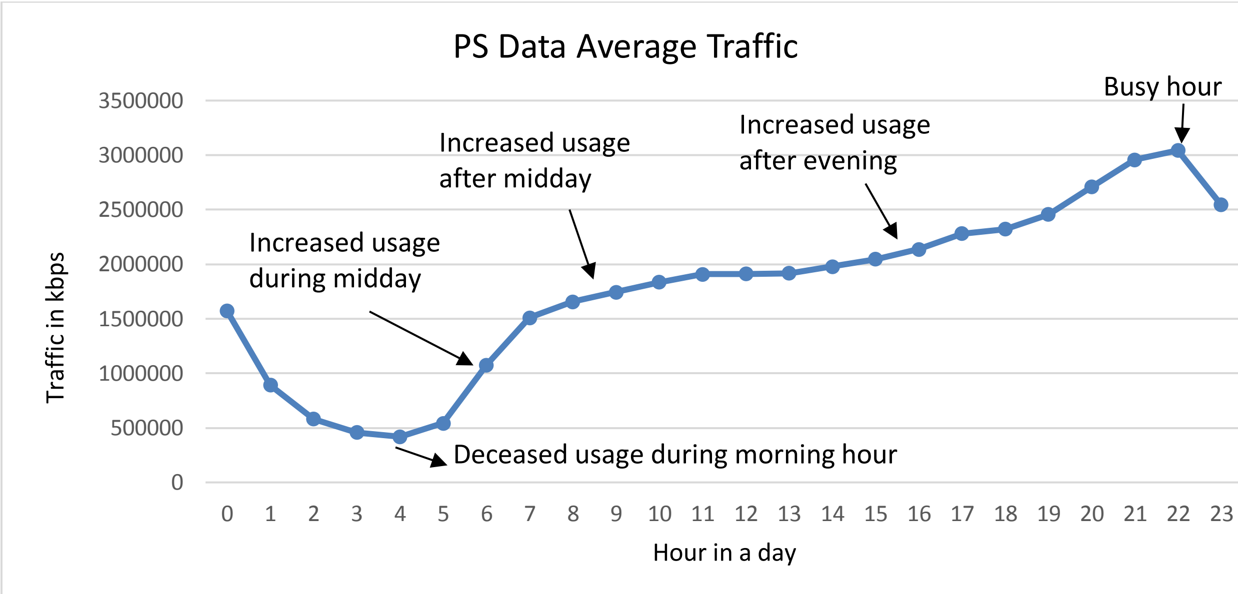

Figure 3-4 PS Average busy hour pattern of May 2016.

3.4.2.2 Busy Hour Traffic Ratio

The ratio of the peak (busy) hour traffic to the total traffic of a day is called busy hour traffic ratio. It is expressed in percentage value. The value will be taken as one user traffic parameter value in capacity analysis.

3.4.2.3 Packet switched Downlink/Uplink ratio

Downlink ratio is the ratio of total downlink traffic to the total throughput traffic, and similarly uplink ratio is the ratio of total uplink traffic to the total throughput traffic. These two ratio values are also a determinant factor of our capacity analysis result. Ratio values used in user traffic profile have to be chosen with a great care since they highly affect and can alter the analysis calculation result.

3.5 CAPACITY PLANNING DETAILS

We have to have two major input parameters in our capacity planning analysis, subscriber number and user traffic usage (profile). These parameters are determinant factors in the mathematical calculation to set the total traffic load per cell. The deployed network input assumption user traffic values are considered theoretically. But, this thesis determine this values based on real time measurement values and present a forecasted value that will help the operator to predict its traffic ahead of time. This will help ethio telecom to serve its customers with a good quality of service and will help to increase its revenue.

3.5.1 Subscriber Analysis

- ✓ UMTS Total subscriber is obtained from the forecasted result.
- ✓ Active users are assumed to be 70% of the total subscribers.

The forecasted UMTS subscriber and active user ratio percentage assumptions made by the operator are directly used in this paper.

3.5.2 Traffic model

The below traffic model is considered by the operator in capacity planning detail analysis.

Assumptions:

- ✓ Voice Per user at busy hour Erlang value = 0.025 Erlang.
- ✓ Heavy user load (with dongle) = 10 GB / month /user.
- ✓ Smart phone load = 1GB /month/user.
- ✓ The busy hour percentage ratio is considered as 10% from the daily traffic.
- ✓ User packet data throughput at busy hour shares 35% from heavy load and 65% from smart phone.

- ✓ Down link ratio is considered as 70% and uplink ration as 30%.
- ✓ Active users are assumed to be 70% of the total subscriber.
- ✓ Traffic per user is assumed as it includes normal traffic, signaling traffic and additional soft handover traffic.
- ✓ Smart phone voice excludes additional soft handover traffic.

Table 3-1 UMTS traffic usage model.

Traffic Usage in GB/Month/User	HSPA+		Voice
	Dongle (in GB/Month)	Smart Phone (in GB/Month)	Smart Phone (in Erlang)
Traffic per user per month	10	1	0.025

Using real time traffic history measurement data and the developed forecasting model, the objective of this paper is to determine an optimum value for the main parameters that are used in the traffic model. These are

1. Busy Hour traffic ratio: 10% is the value used in the deployed planning.
2. Down link ratio: 70% is the value used in the deployed planning.
3. Uplink ration: 30% is the value used in the deployed planning.
4. Voice traffic at busy hour Erlang value: 0.025 Erlang is the value used in the deployed planning.

3.5.3 Mathematical detail in capacity planning

Since the voice unit is in Erlang, it should be converted to Kbps. Bandwidth estimation for a connection which uses compressed speech can be calculated by Activity Factor (AF).

$$\mathbf{BW} = \mathbf{AF} \times \mathbf{R} \tag{3.1}$$

Where

BW is Bandwidth.

AF is Percentage of Activity Factor.

R is Bearer or Services bit rate.

The busy hour voice traffic equivalent in user volume is:

$$\mathbf{V_{bh}} = \mathbf{U} * \mathbf{Activity\ Factor} * \boldsymbol{R} \tag{3.2}$$

Where

V_{bh} is Volume per user at busy hour.

U is Erlang per user at busy hour.

Note that different services have different service rate and activity factor. The below table shows service rate and activity factor.

Table 3-2 Service rate and activity factor.

Service Type	R(Service Rate)	Activity Factor
Adaptive multi rate (AMR)	12.2kbps	0.67
Video phone (CS64)	64kbps	1
PS services		0.9

From the heavy data and Smart phone usage, average user throughput at busy hour is calculated as shown below.

$$\mathbf{Heavy\ User\ usage/month/user} = (\mathbf{35\%} * \mathbf{heavy\ load/month}) \tag{3.3}$$

$$\mathbf{Smart\ phone\ PS\ usage/month/user} = (\mathbf{65\%} * \mathbf{smart\ phone/month} \tag{3.4}$$

$$\textbf{Heavy User usage/user/day} = (\textbf{Heavy User usage/month/user})/\textbf{30days} \tag{3.5}$$

$$\textbf{Smart phone User usage/user/day} = (\textbf{Smart phone PS usage/month/user})/\textbf{30days} \tag{3.6}$$

$$\textbf{Active Heavy User usage/user/day} = (\textbf{Heavy User usage/user/day}) * \textbf{70}\% \tag{3.7}$$

$$\textbf{Active Smart phone User usage/user/day} = (\textbf{Smart phone User usage/user/day}) * \textbf{70}\ \% \tag{3.8}$$

$$\textbf{Active Heavy User usage/user/day at busy hour} = \textbf{Active Heavy User usage/user/day} * \textbf{10}\ \% \tag{3.9}$$

$$\textbf{Active Smart phone User usage/user/day at busy hour} = (\textbf{Active Smart phone User usage/user/day} * \textbf{10}\%) + \textbf{Volume per user at busy hour} \tag{3.10}$$

$$\textbf{Average User throughput at busy hour} = \textbf{Active Heavy User usage/user/day at busy hour} + \textbf{Active Smart phone User usage/user/day at busy hour} \tag{3.11}$$

The above equations, from (3.1) up to (3.11), are the basic calculation that our capacity planning is based on. These equations are also the back bone of cell load analyzer tool. Cell load analyzer is a tool prepared to this work with the above algorithms. The forecasting result from the forecasting model will be analyzed with this tool. Description about the tool is presented in Chapter 5. In the next Chapter, forecasting which is based on Artificial Neural Network will be presented.

4. ARTIFICIAL NEURAL NETWORK-based CAPACITY PLANNING

4.1 OVERVIEW

Capacity planning is concerned mainly with the future performance of the network. For capacity planning, the workload is forecasted based on long term monitoring of the system. Measurements in the UMTS networks allow us to forecast how the network is going to grow and what capacity upgrades are going to be required. Therefore, this workload characterization is done based on collected UMTS measurements.

Operators have to predict the future traffic, and based on obtained result they can develop their planning and marketing policy. A good forecast will help the operator to exploit all resources and protect them from dissatisfied customers.

In this thesis, a forecasting model is used to determine user traffic profile pattern of UMTS network ahead of time for Addis Ababa city. Using the ethio telecom performance data, user traffic profile is predicted with Artificial Neural Network (ANN). The performance data collected from the real system is given to this model as an input/output for training.

4.2 ARTIFICIA NEURAL NETWORK

ANN is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information [2626][27]. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. ANNs, like people, learn by example [28][27]. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons. This is true of ANNs as well.

Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. A trained neural network can be thought of as an "expert" in the category of information it has been given to analyze. This expert can then be used to provide projections, given new situations of interest, and answer "what if" questions.

Other advantages include:

1. Adaptive learning: An ability to learn how to do tasks based on the data given for training or initial experience.
2. Self-Organization: An ANN can create its own organization or representation of the information it receives during learning time.
3. Real Time Operation: ANN computations may be carried out in parallel, and special hardware devices are being designed and manufactured which take advantage of this capability.
4. Fault Tolerance via Redundant Information Coding: Partial destruction of a network leads to the corresponding degradation of performance. However, some network capabilities may be retained even with major network damage [29][2626][27].

4.2.1 ARCHITECTURE OF NEURAL NETWORKS

4.2.1.1 Feed-forward networks

Feed-forward ANNs allow signals to travel one way only; from input to output. There is no feedback (loops) i.e. the output of any layer does not affect that same layer. Feed-forward ANNs tend to be straight forward networks that associate inputs with outputs. They are extensively used in pattern recognition. This type of organization is also referred to as bottom-up or top-down [30][26].

4.2.1.2 Feed-back networks

Feedback networks can have signals travelling in both directions by introducing loops in the network. Feedback networks are very powerful and can get extremely complicated. Feedback networks are dynamic; their 'state' is changing continuously until they reach an equilibrium point. They remain at the equilibrium point until the input changes and a new equilibrium needs to be found. Feedback architectures are also referred to as interactive or recurrent, although the latter term is often used to denote feedback connections in single-layer organizations [31][30][2626].

4.2.2 NETWORK LAYERS

“Neural network” (NN) and “artificial neural network” (ANN) usually refer to a multilayer perceptron network [33]. The common type of artificial neural network consists of three groups, or layers, of units: a layer of "input" units is connected to a layer of "hidden" units, which is connected to a layer of "output" units (refer Figure 4.1) [34][35][2626].

- ✓ The activity of the input units represents the raw information that is fed into the network.
- ✓ The activity of each hidden unit is determined by the activities of the input units and the weights on the connections between the input and the hidden units.

- ✓ The behavior of the output units depends on the activity of the hidden units and the weights between the hidden and output units.

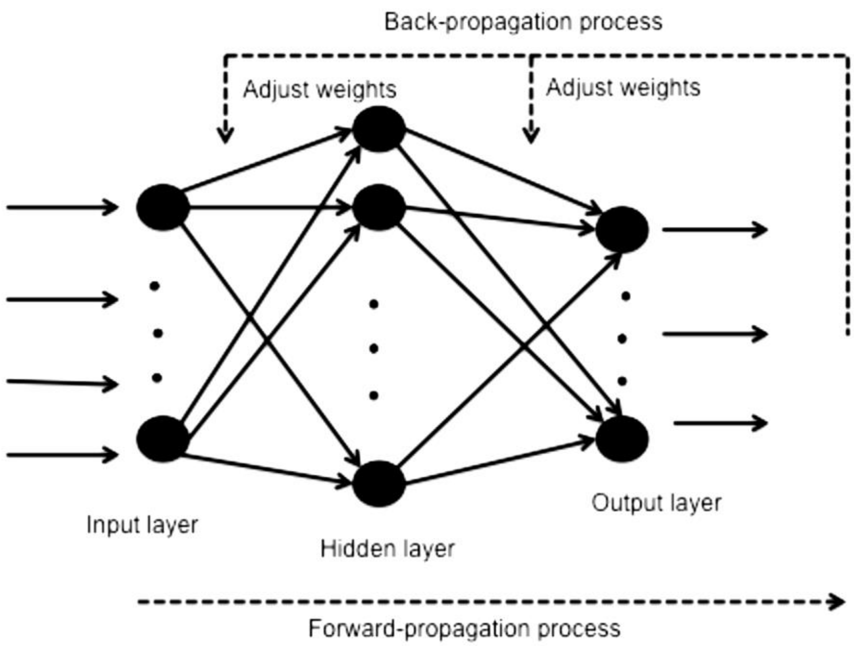

Figure 4-1 Feed forward neural network structure with back-propagation algorithm [32].

Simple type of network is interesting because the hidden units are free to construct their own representations of the input. The weights between the input and hidden units determine when each hidden unit is active, and so by modifying these weights, a hidden unit can choose what it represents.

Neural networks are also distinguish as single-layer and multi-layer architectures. The single-layer organization, in which all units are connected to one another, constitutes the most general case and is of more potential computational power than hierarchically structured multi-layer organizations. In multi-layer networks, units are often numbered by layer, instead of following a global numbering.

4.2.3 THE LEARNING PROCESS

All learning methods used for adaptive neural networks can be classified into two major categories: Supervised learning and unsupervised learning.

- ✓ Supervised learning

Which incorporates an external teacher, so that each output unit is told what its desired response to input signals ought to be. During the learning process global information may be required. Paradigms of supervised learning include error-correction learning, reinforcement learning and stochastic learning [36].

An important issue concerning supervised learning is the problem of error convergence, i.e. the minimization of error between the desired and computed unit values. The aim is to determine a set of weights which minimizes the error. One well-known method, which is common to many learning paradigms, is the least mean square (LMS) convergence.

- ✓ Unsupervised learning

Uses no external teacher and is based upon only local information. It is also referred to as self-organization, in the sense that it self-organizes data presented to the network and detects their emergent collective properties. We say that a neural network learns off-line if the learning phase and the operation phase are distinct. A neural network learns on-line if it learns and operates at the same time. Usually, supervised learning is performed off-line, whereas unsupervised learning is performed on-line [36].

4.2.3.1 Transfer Function

The behavior of an ANN depends on both the weights and the input-output function (transfer function) that is specified for the units. This function typically falls into one of three categories:

- ✓ linear (or ramp)

- ✓ threshold
- ✓ sigmoid

For **linear units**, the output activity is proportional to the total weighted output. For **threshold units**, the output are set at one of two levels, depending on whether the total input is greater than or less than some threshold value. For **sigmoid units**, the output varies continuously but not linearly as the input changes. Sigmoid units bear a greater resemblance to real neurons than do linear or threshold units, but all three must be considered to do rough approximations [37][38]].

To make a neural network that performs some specific task, we must choose how the units are connected to one another (see Figure 4.1), and we must set the weights on the connections appropriately. The connections determine whether it is possible for one unit to influence another. The weights specify the strength of the influence.

We can teach a three-layer network to perform a particular task by using the following procedure:

1. We present the network with training examples, which consist of a pattern of activities for the input units together with the desired pattern of activities for the output units.
2. We determine how closely the actual output of the network matches the desired output.
3. We change the weight of each connection so that the network produces a better approximation of the desired output [39].

4.2.3.2 The Back-Propagation Algorithm

In order to train a neural network to perform some task, we must adjust the weights of each unit in such a way that the error between the desired output and the actual output is reduced. This process requires that the neural network compute the error derivative of the weights (EW). In other words, it must calculate how the error changes as each weight is increased or decreased slightly. The back propagation algorithm is the most widely used method for determining the EW.

The back-propagation algorithm is easiest to understand if all the units in the network are linear. The algorithm computes each EW by first computing the EA, the rate at which the error changes as the activity level of a unit is changed. For output units, the EA is simply the difference between the actual and the desired output. To compute the EA for a hidden unit in the layer just before the output layer, we first identify all the weights between that hidden unit and the output units to which it is connected. We then multiply those weights by the EAs of those output units and add the products. This sum equals the EA for the chosen hidden unit. After calculating all the EAs in the hidden layer just before the output layer, we can compute in like fashion the EAs for other layers, moving from layer to layer in a direction opposite to the way activities propagate through the network. This is what gives back propagation its name. Once the EA has been computed for a unit, it is straight forward to compute the EW for each incoming connection of the unit. The EW is the product of the EA and the activity through the incoming connection.

Note that for non-linear units the back-propagation algorithm includes an extra step. Before back-propagating, the EA must be converted into the EI, the rate at which the error changes as the total input received by a unit is changed [40][2626].

4.3 MODEL IMPLEMENTATION

The time series neural network model prepared for this study uses non-linear autoregressive (NAR) method. The future values of a time series $y(t)$ are predicted only from d past values of that series. This form of prediction is called nonlinear autoregressive, or NAR, and can be written as follows:

$$\mathbf{y(t) = f(y(t-1) \ldots\ldots\ldots y(t-d))} \tag{4.1}$$

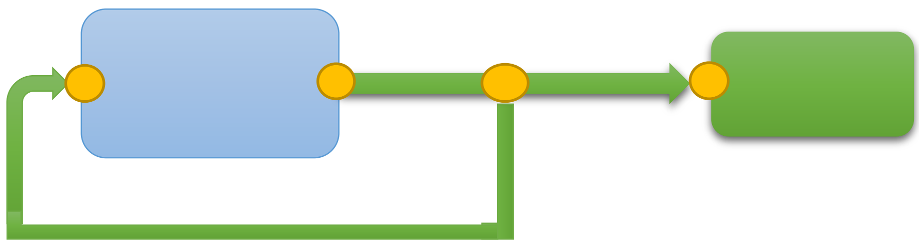

Figure 4-2 Nonlinear Autoregressive (NAR).

A multistep forecasting model design is shown in Figure 4-3. This is a typical model design that the input layer consists the 24 hour's input data. 10 neurons are considered in the hidden layer. Hidden layer uses sigmoid transfer function, the output varies continuously but not linearly as the input changes. Sigmoid units bear a greater resemblance to real neurons than do linear or threshold units. The output layer consists 24 predicted values.

The model uses no external teacher and is based upon only local information which is defined as unsupervised learning. W and b represents the weights and bias values that are connected to each neuron in the layers. Prediction can be done for one step ahead and multistep ahead. In one step ahead prediction, only the next time step forecasted value will be determined. Where as in multistep, any number of (N = positive integer) future time steps can be predicted. It is obvious that, the length of the collection period of the real time traffic data will have a great impact in forecasting process to determine an appropriate value for the number of future time steps (N).

In this study the maximum history data that cab be collected from the system is 14 consecutive months of user traffic data. From the collected data, the result and discussion part tries to present and describe the future user traffic trend for two N values of future time steps, N=1 year (the next twelve consecutive months) and N=5 year (the next 60 consecutive months).

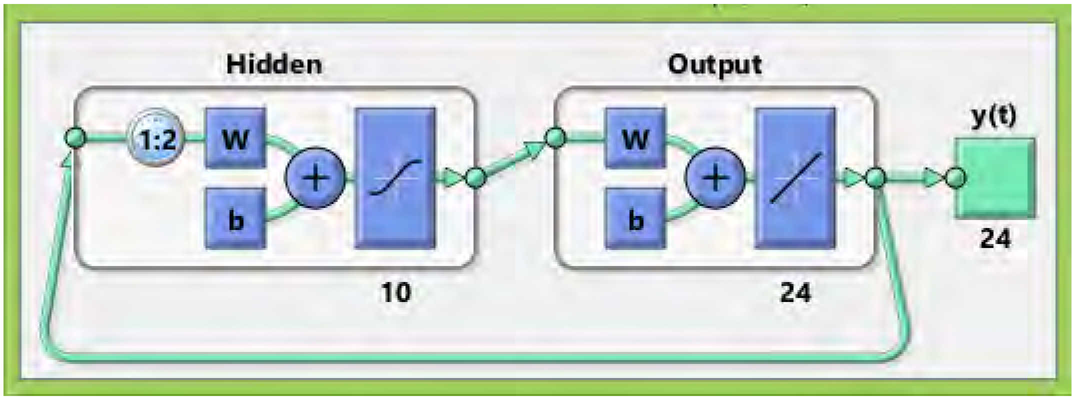

Figure 4-3 Atypical multi step forecasting model example.

Based on the model implemented in MATLAB, observations are the focuses of the next chapter. Based on the forecasted result obtained from the artificial neural network model, the user traffic profile of Addis Ababa UMTS network will be determined. The details of the step ahead forecasting user traffic values and the analyzer tool cell load results are the main points of the result and discussion section.

5. RESULTS AND DISCUSSION

The ability to model and perform decision and analysis is an essential feature of many real-world applications [41]. From the different problem solving models, time series is the one which is used in forecasting. Time series analysis comprises methods for analyzing time series data in order to extract meaningful statistics and other characteristics of the data. Time series forecasting is the use of a model to predict future values based on previously observed values. This technique usually uses historical data using statistical principles and concepts for only the variable of interest to forecast its future values.

5.1 TRAFFIC PROFILE FORECASTING FLOW CHART

The ANN model designed in MATLAB can perform two types of forecasting, one-step ahead and multi-step ahead. As it has been seen in the previous Chapter, in one step ahead, the model forecasts only the next time step value where as in multi-step the model can forecast N (can take any positive integer value) time steps ahead. In this thesis, we used two N values. N = 12 months to predict for the coming one year and N = 60 months for the coming five years. The obtained data from the performance reporting system (PRS) is combined in Excel and given to the model for training. From the trained model, we predict the future time step series values. Figure 5.1 shows the flow chart of the forecasting process.

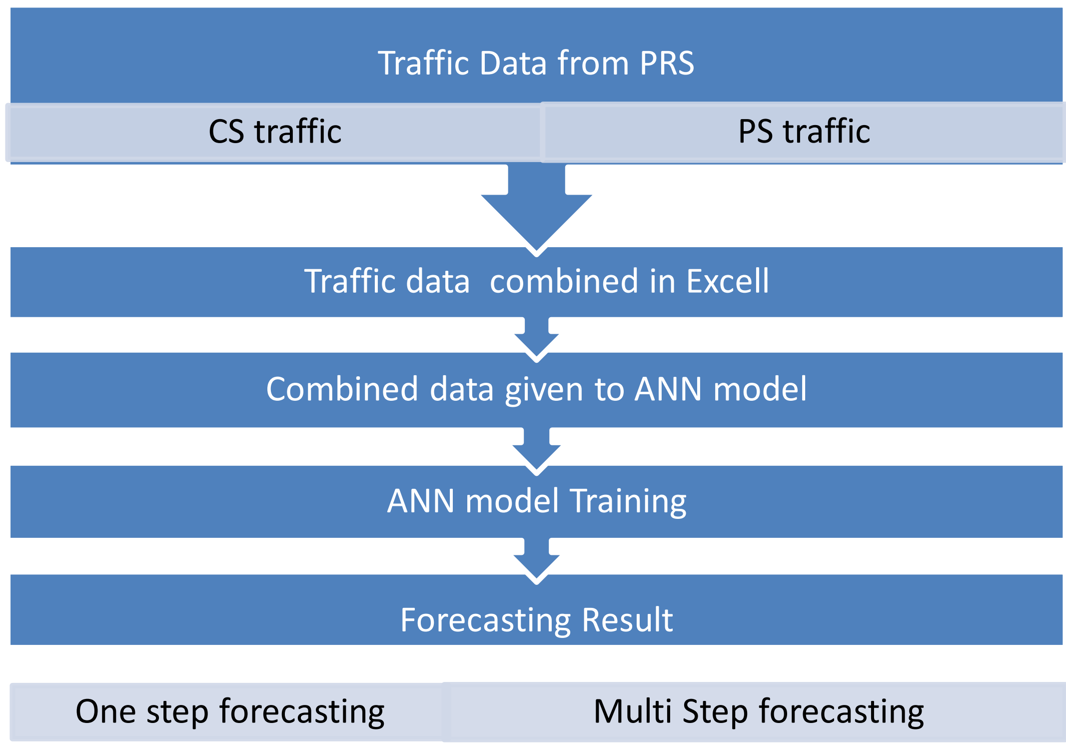

Figure 5-1 Forecasting flow chart.

The user traffic parameter result from the forecasting process which are the focuses of this thesis are:

I. **Traffic variation and busy hour (BH) traffic determination**

The user traffic distribution over 24 Hours in a day are combined to give a cumulative average in a monthly basis traffic pattern. The collected voice and data traffic characteristics for each month is demonstrated with graphs. From the average traffic pattern, the busy hour will be determined.

II. **Busy hour traffic ratio**

One of the user profile parameter used as an input assumption value in capacity planning is user busy hour ratio. It is the ratio of the user busy hour traffic to the total user traffic of a day (24 hour).

III. **Down link and Uplink traffic ration**

User traffic is an aggregate result of downlink and uplink. In capacity analysis the downlink and uplink ratio value will determine the capacity result. So, proper ratio value between uplink and downlink has to be settled in order to determine a proper dimensioning in the network element.

IV. **Voice and data traffic per user value (Erlang per user)**

This is an average value of traffic that a single user is expected to share from the total traffic at busy hour. The single user traffic will multiply to the total forecasted subscriber number to get the total load of the busy hour traffic. Voice traffic per single user and data traffic per individual will be combined to know the total demand of a user at busy hour.

Each user traffic profile which are under the scope of this thesis work will be discussed based on their future forecasted values of one-step and multi-step ahead prediction result. In the traffic analysis, the voice traffic (in CS domain) and the data traffic (in PS domain) are presented and measurements further elaborates with graphs using each user traffic distribution with a monthly average values for each 24 hours.

5.2 BUSY HOUR DETERMINATION

The traffic varies according to different activity in the society. The traffic is generated by single source, subscribers who normally make telephone calls or data services on their end devices. Measurement analysis of the traffic variations shows that it is partly of a stochastic nature and partly of a deterministic nature.

5.2.1 CS Traffic variations and busy hour

Figure 5.2 shows the CS traffic pattern variation of 14 consecutive months. Averaging the monthly collected data over the 24 hours period of a day and comparing these months of average measurement data, we can recognize a deterministic curve with overlying stochastic variations. During a 24 hours period, the average Addis Ababa voice traffic pattern looks as shown in Figure 5.3. The horizontal axis represents 24 hours and the vertical axis describes the user traffic in Erlang.

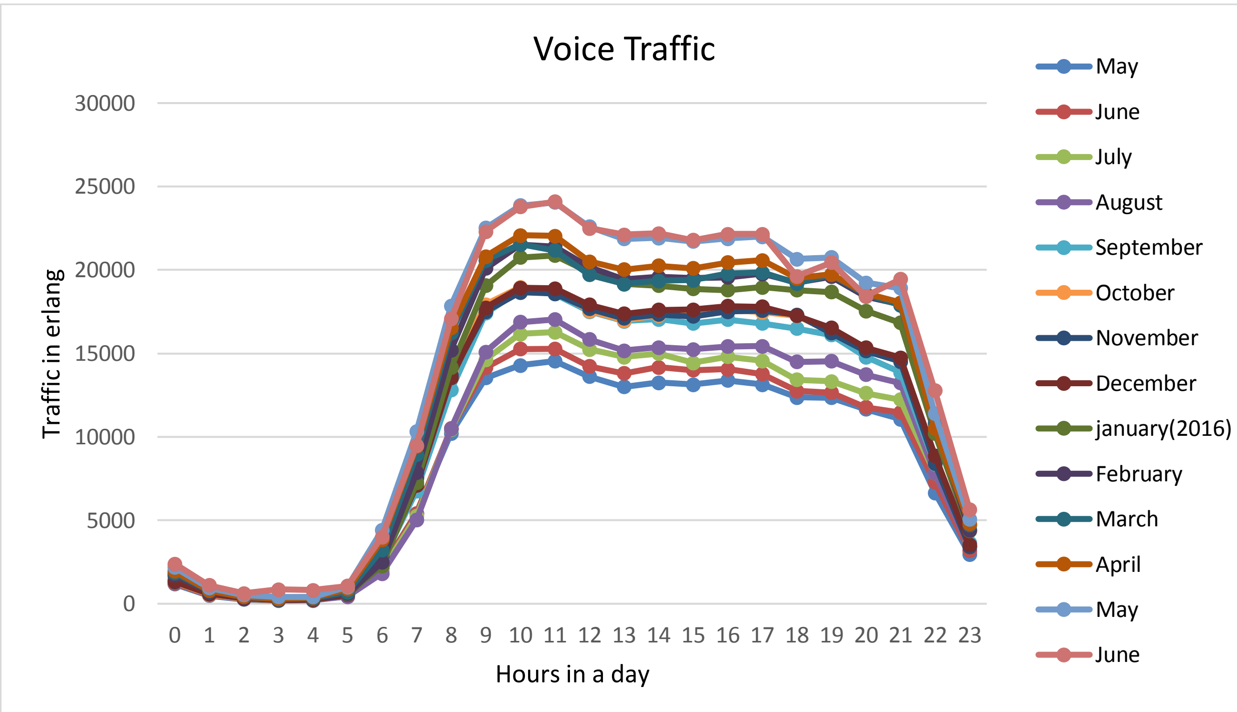

Figure 5-2 CS voice traffic pattern from May 2015 to June 2016.

As shown in the Figure 5.3, the busy hour (peak value) occurred in the morning time. Two peak values with a very close measurement are observed before midday. The first peak value occurred at 11:00 (from 10:00 to 11:00) and the second occurred nearly at the first busy hour time at 10:00 (from 9:00 to 10:00). After midday, we see a quite similar usage with a slowly decreasing trend until evening 21:00.

From the average voice traffic pattern, people make more consistent voice calls in the afternoon than in the morning. This might be expected since in the working hours people use more voice calls for their business and office activities. However, the peak busy hour is observed in the morning time.

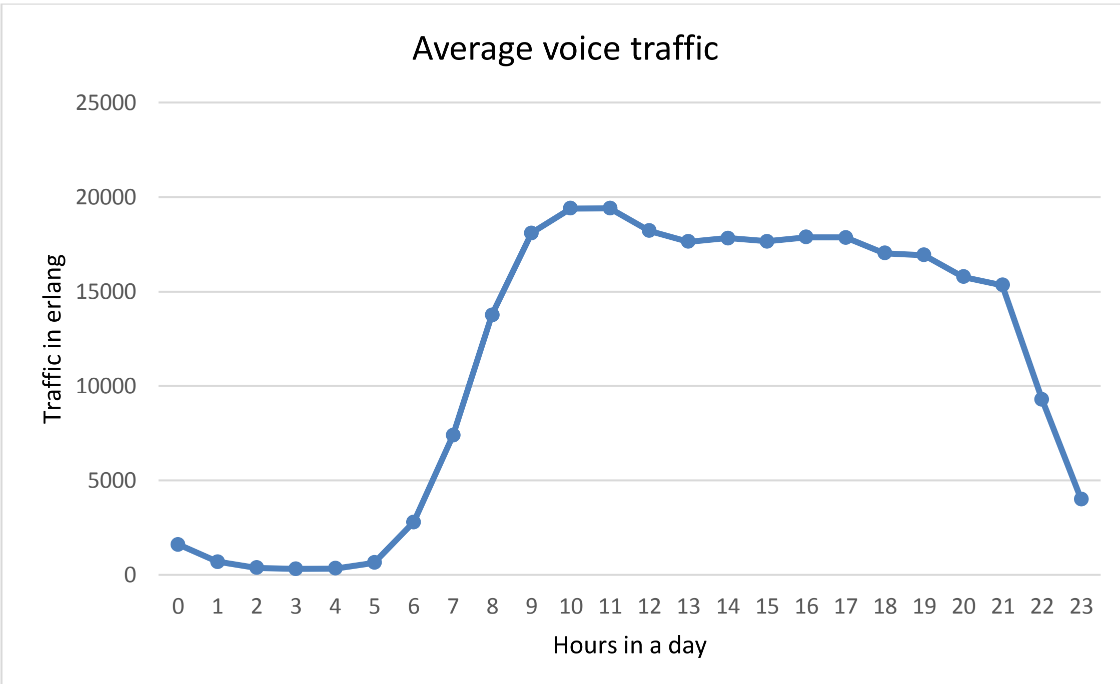

Figure 5-3 Average voice traffic pattern (from May 2015 to June 2016).

5.2.2 PS Traffic variations and rush hour

On the contrary to the voice traffic pattern, its busy hour occurred in the morning, the data throughput pattern decreases in the morning until midday. After midday, it increases and reaches its rush hour near mid night at 22:00 (from 21:00 -22:00). This time period is when the majority of data users are online or accessing the data service at the same time. It is the evening time when most users settle and access the internet at home after having completed their travel, shopping, dinner and other responsibilities.

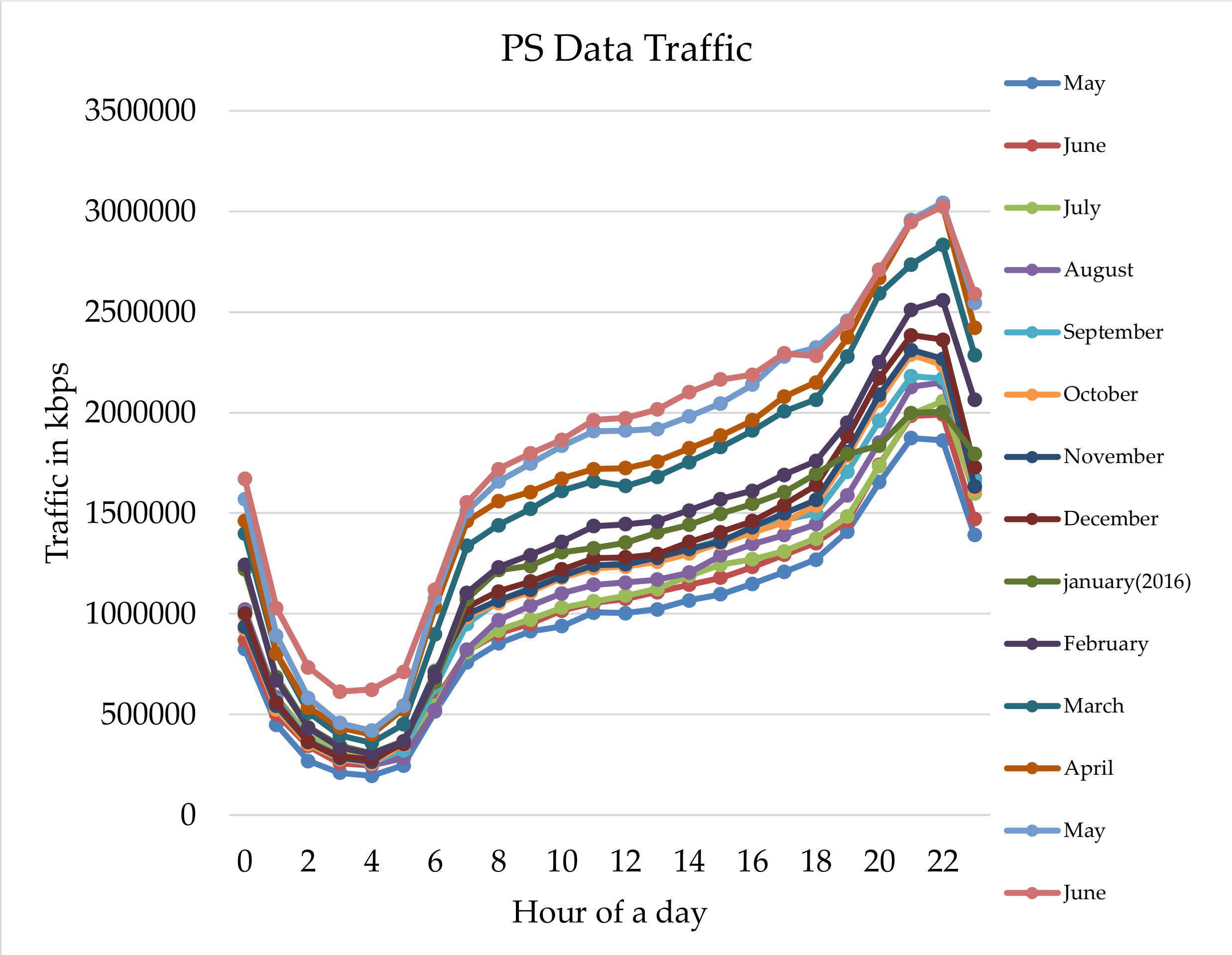

Figure 5-4 PS data traffic pattern from May 2015 to June 2016.

In addition, mobile devices with a better browsing capability and application software will allow the user to access internet with always-available connectivity in their free time (refer Figure 5.5). So, for the Internet service provider, this is a time of heavy load, and a corresponding time of bandwidth assurance is enquired to ensure smooth flow and a connection free of bottlenecks. The network has to support this busy hour.

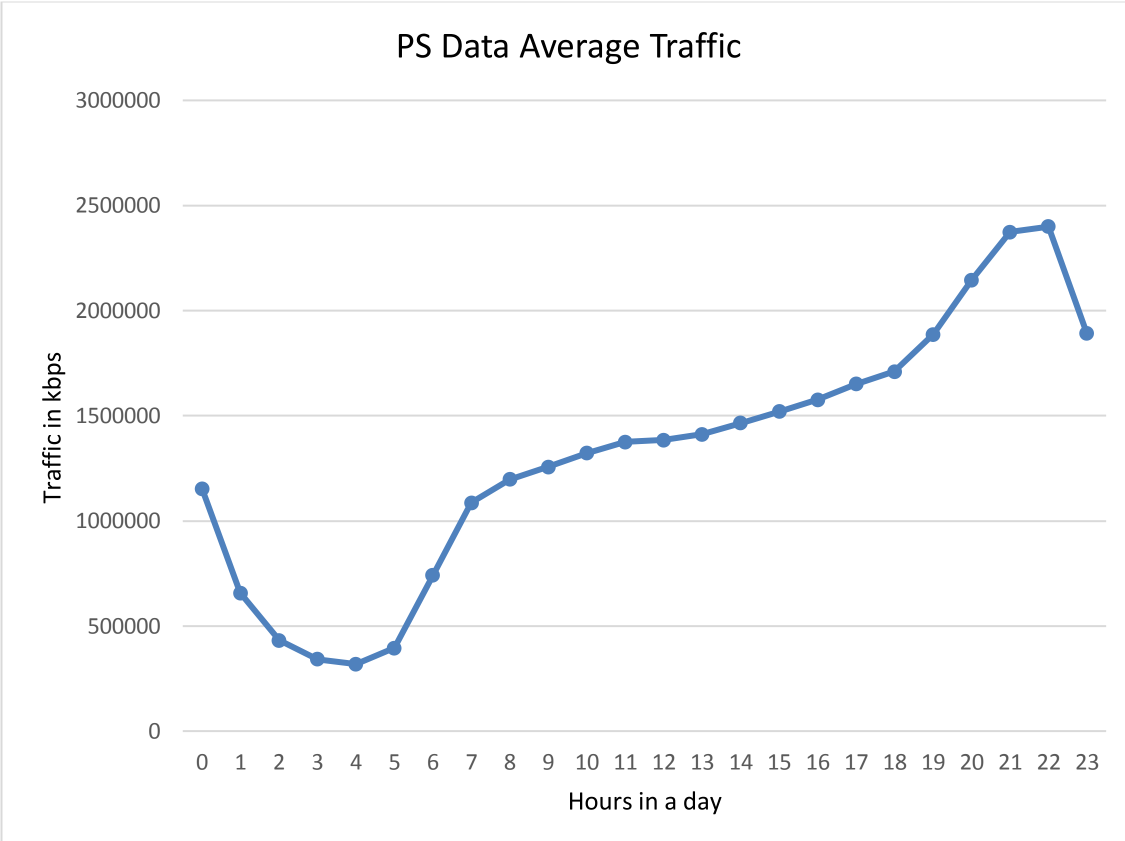

Figure 5-5 PS Average data traffic (from May 2015 to June 2016).

5.3 CS and PS BUSY HOUR TRAFFIC RATIO

The CS BH ratio (busy hour traffic per total traffic of a day) graph shows the maximum peak value occurred in August with 7.43% (Figure 5.6). For the packet switch throughput the maximum peak value occurred in May 2015 with 8.08% (Figure 5.6). We use the maximum BH ratio value in capacity planning. So, the maximum percentage value, determined in the BH forecasted result, is used in our analysis tool.

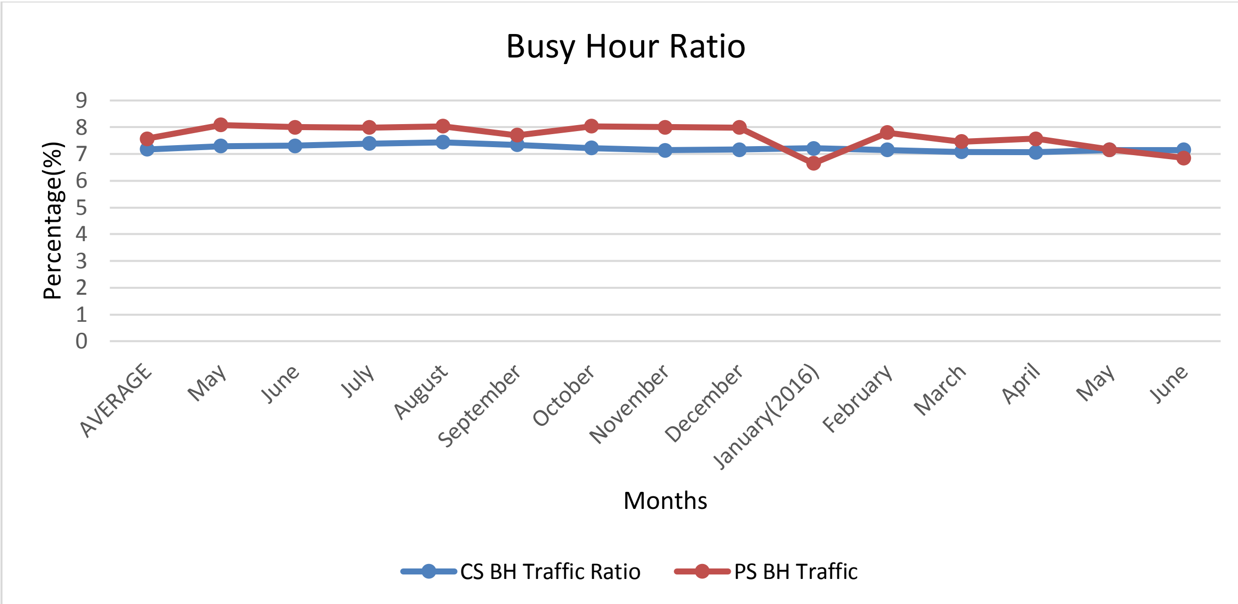

Figure 5-6 CS and PS busy hour traffic ratio from May 2015 to June 2016.

In one step ahead prediction, the maximum BH ratio value is 7.87% (Figure 5.7). In the multi-step prediction, 8.46% is the maximum value for N=12 months and 8.47% for N=60 months (Figure 5.7).

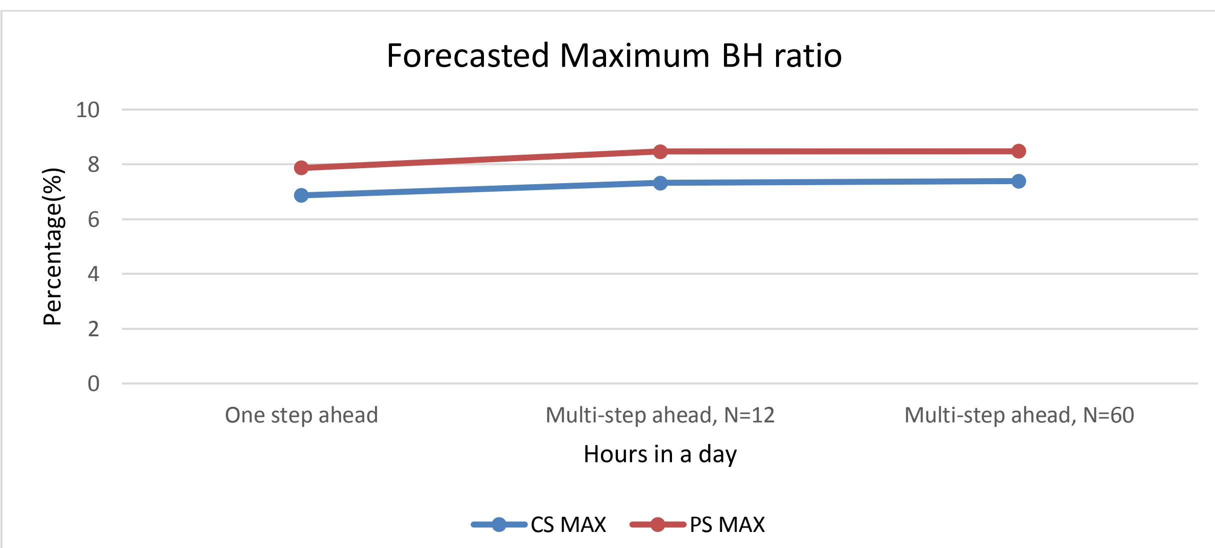

Figure 5-7 CS and PS busy hour average and maximum traffic ratio.

Average value of the forecasted result is shown in figure 5-8 for comparison. Packet switch busy hour ratio has a higher peak value than circuit switch traffic both in maximum and average BH ratio.

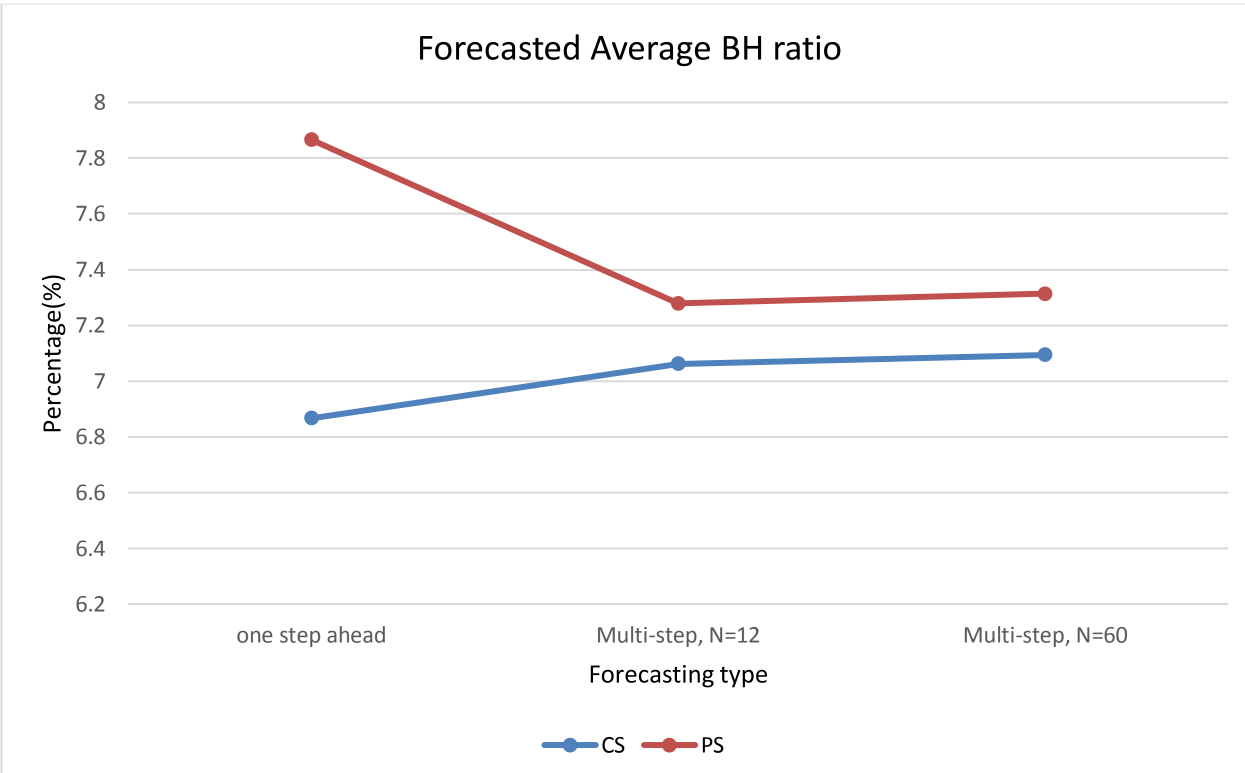

Figure 5-8 Forecasted average and maximum busy hour ratio.

5.4 BUSY HOUR DOWNLINK/UPLINK TRAFFIC RATIO

As the collected data describes (Figure 5.10 and 5.13), the average downlink ratio varies with a minimum ratio value of 79.15% and with a maximum ratio value of 82.95%. The uplink data also varies in the range with minimum value 17.05% and maximum value of 20.85%. Their average percentage ratio will be used in our capacity dimensioning analysis. The average downlink and uplink forecasted results are shown in Figure 5.11 and 5.14.

5.4.1 PS downlink ratio

The downlink traffic characteristics of user usage in the collected period time is shown in Figure 5-9 in a monthly average data. The average downlink busy hour ratio is measured as 80.81%.

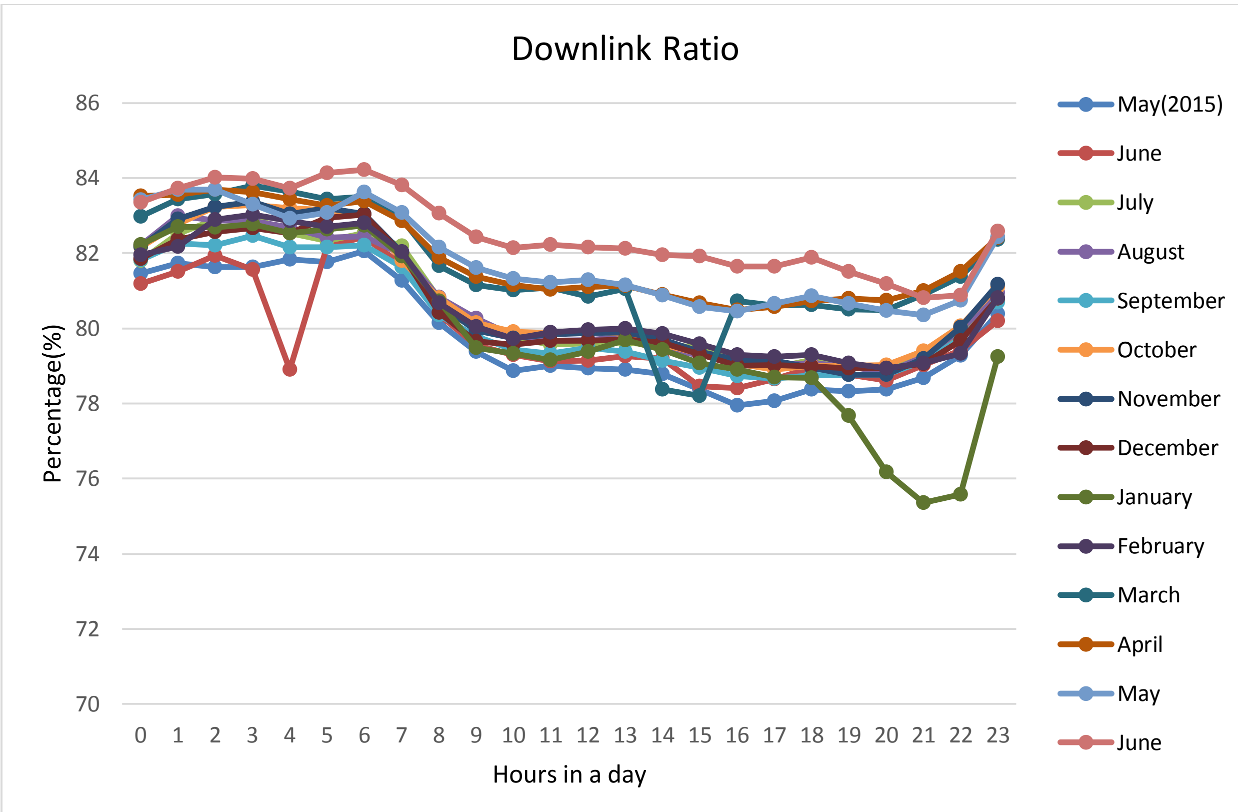

Figure 5-9 Down link ratio from May 2015 to June 2016.

It will be possible to conclude from the average graph of the downlink user traffic profile ratio that from the total traffic of Addis Ababa city subscribers, 80.81% of the traffic is handled by the downlink traffic.

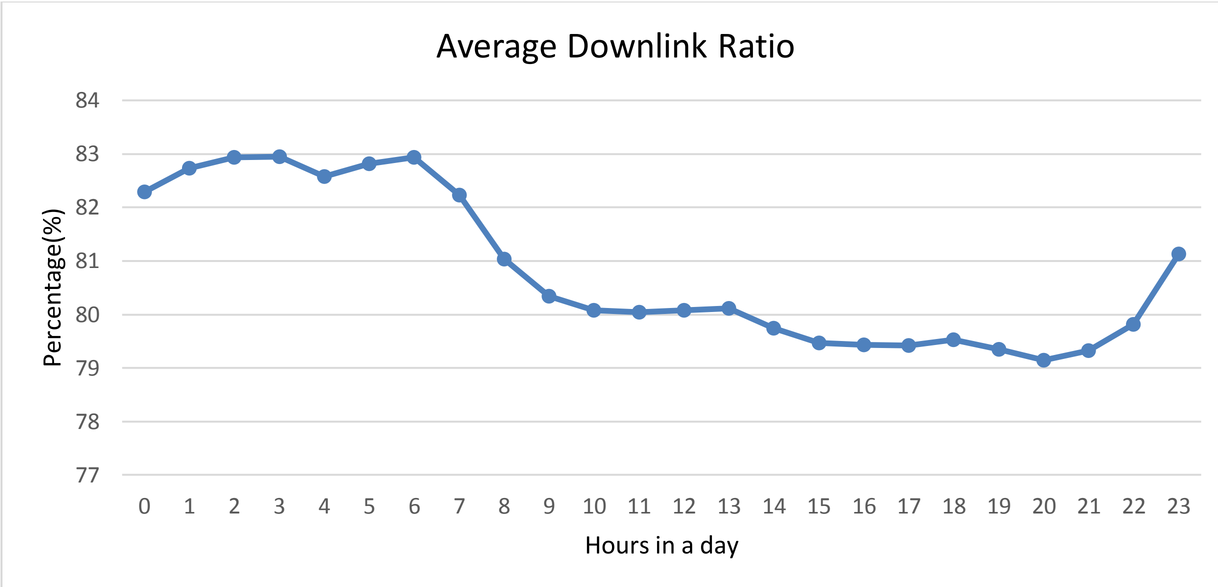

Figure 5-10 Average down link ratio (from May 2015 to June 2016).

In the forecasted data, one step ahead prediction has an average value of 84.18% and multi-step prediction with N= 12 and N = 60 has average values of 80.03% and 79.67% respectively.

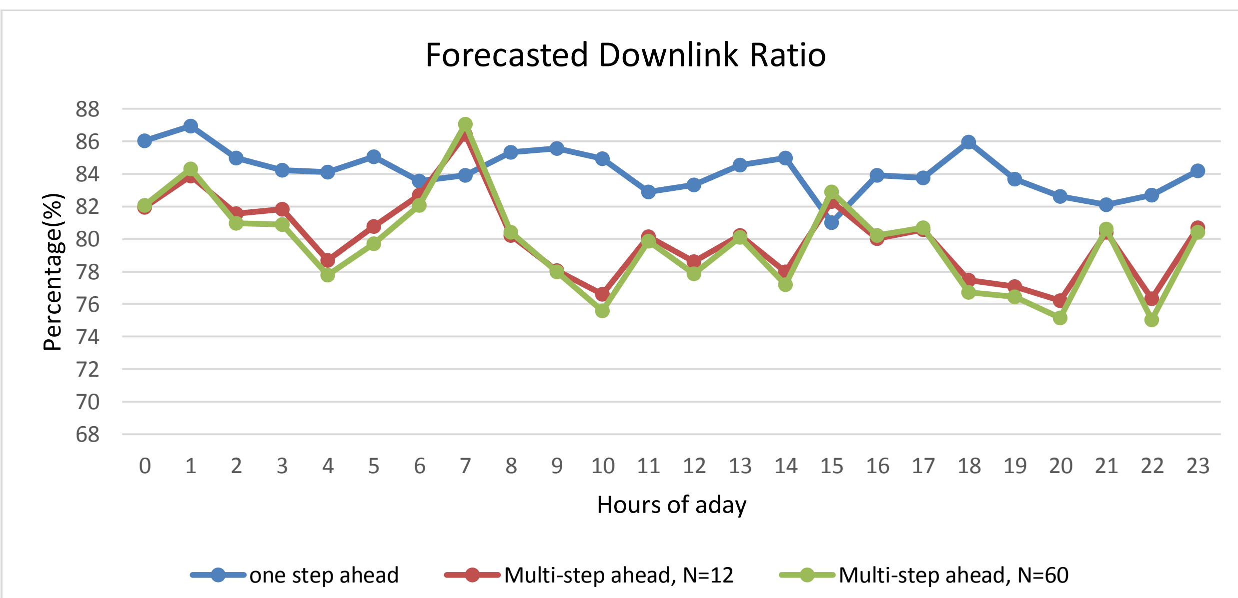

Figure 5-11 Average forecasted downlink ratio for one step and multi-step

5.4.2 PS uplink ratio

In the uplink collected data, the average uplink busy hour ratio is measured as 19.16%. In the forecasted data, one step ahead prediction has an average value of 16.4% and multi-step prediction with N= 12 and N = 60 has average values of 17.4% and 18.47% respectively.

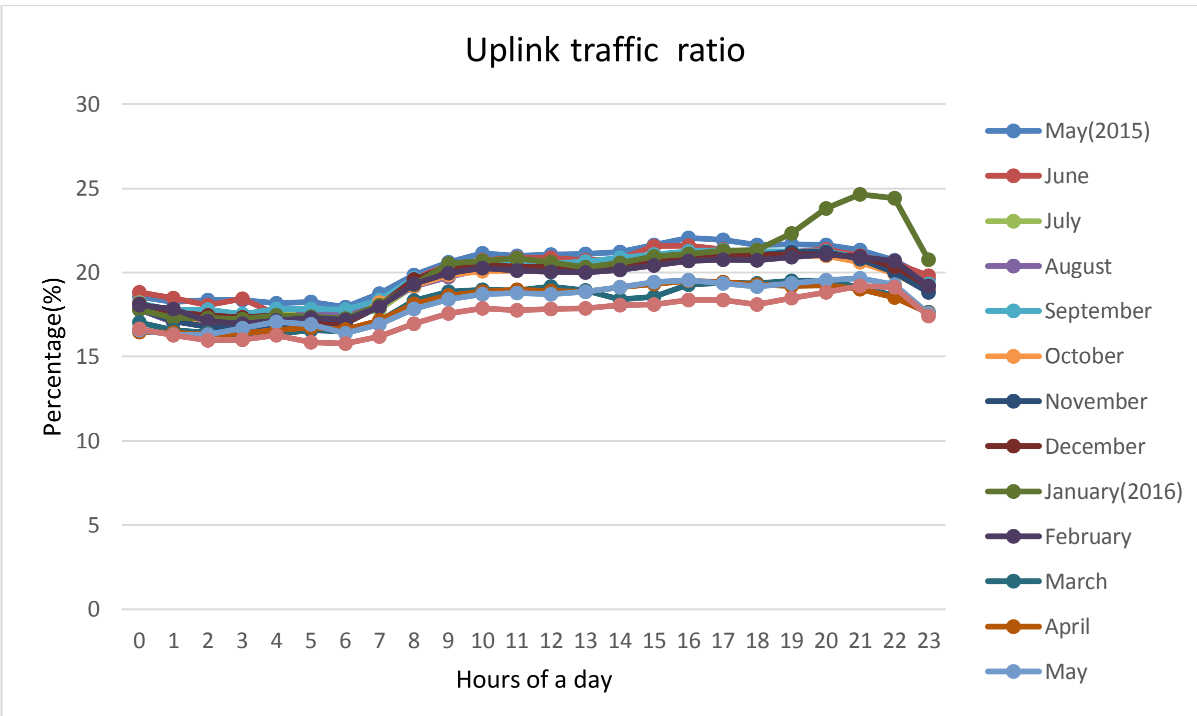

Figure 5-12 Uplink ratio from May 2015 to June 2016.

As indicated in the average uplink traffic ratio, 19.16% of the total traffic is handled in uplink direction. It is reasonable that more traffic is handled by the downlink traffic. A proper ratio in this two directions (downlink and uplink) will help the network element to hold the total traffic load. So, from Figure 5-13 the average uplink traffic ratio of Addis Ababa city is 19.16% of the total traffic.

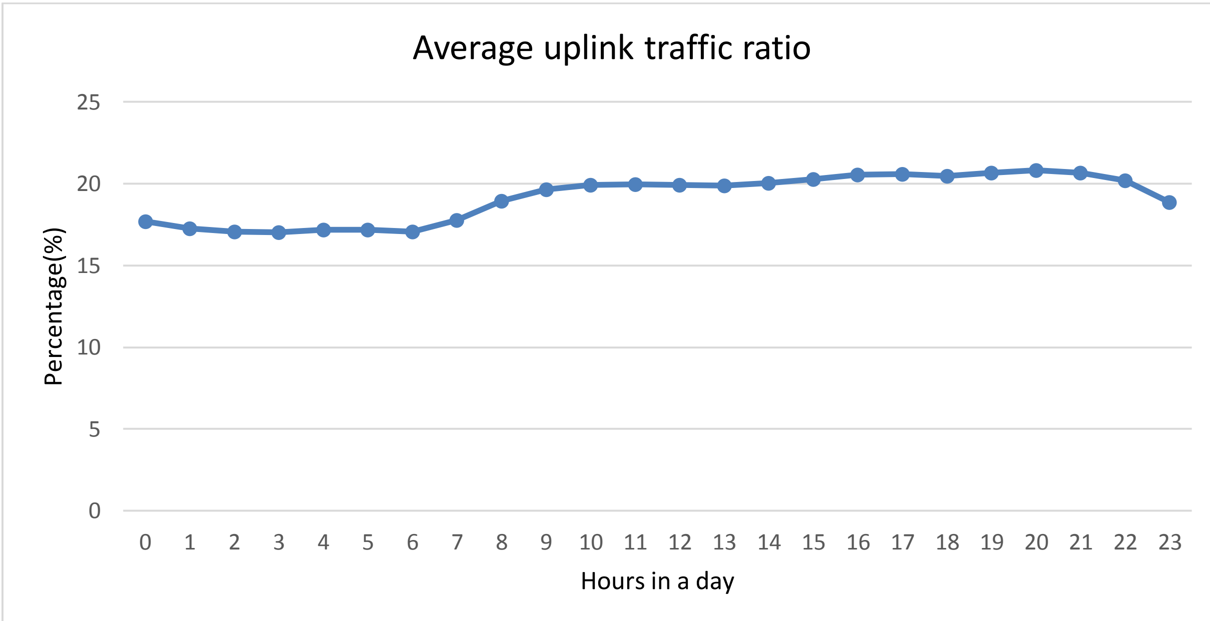

Figure 5-13 Average uplink ratio (from May 2015 to June 2016).

Figure 5-14 shows the result of the uplink traffic forecasted by ANN model. One-step and multi-step predicted values are plotted in the graph.

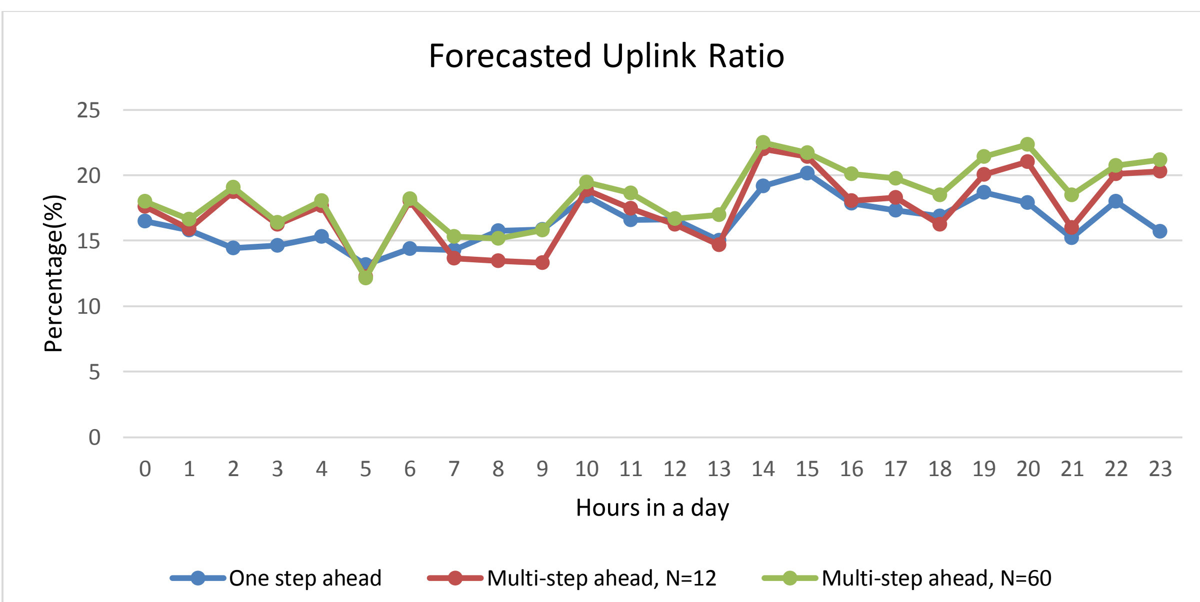

Figure 5-14 Forecasted one step and multi-step ahead uplink ratio.

The average cumulative ratio result obtained from forecasted downlink and uplink ratio is determined as:

- ✓ Based on real time measurement, downlink/uplink ratio (%) = 80.83/19.17
- ✓ Based on one-step ahead forecasting, downlink/uplink ratio (%) = 83.69/16.31
- ✓ Based on multi-step ahead forecasting for N=12, downlink/uplink ratio (%) = 82.14/17.86
- ✓ Based on multi-step ahead forecasting for N=60, downlink/uplink ratio (%) = 82.14/17.86

5.5 VOICE TRAFFIC PER USER

As we observed the busy hour traffic pattern, the voice traffic per user data also follows the same pattern. The voice per user traffic increases in the morning time and reaches its peak value at 11:00 (from 10:00 to 11:00).

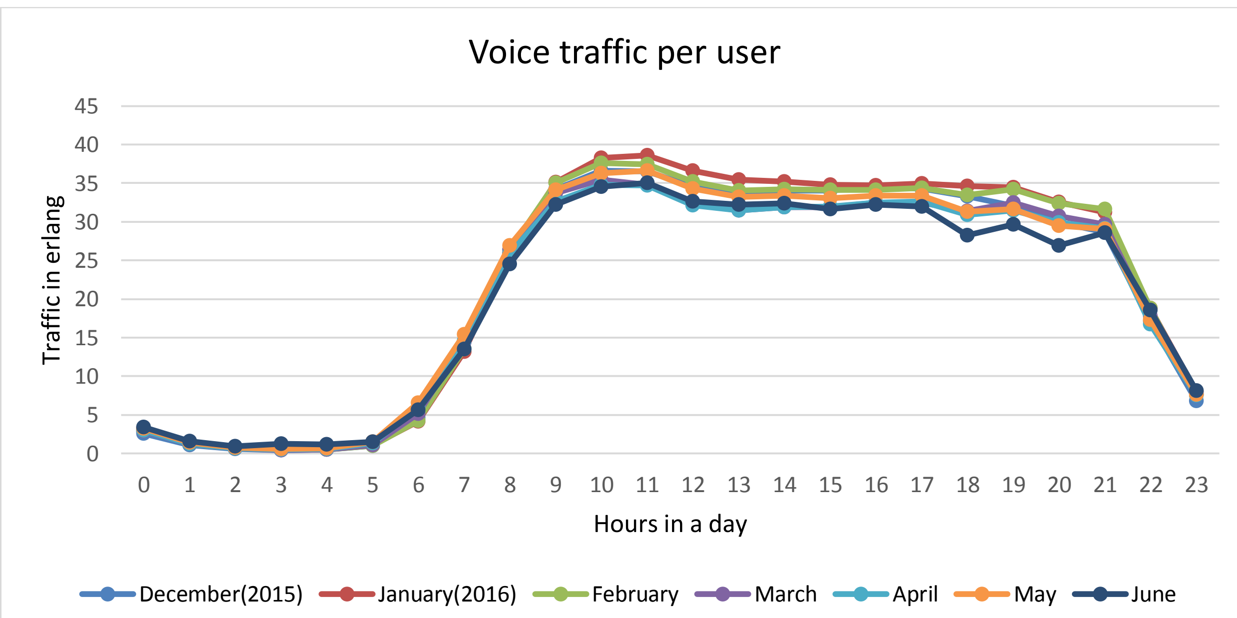

Figure 5-15 Voice traffic per user from December 2015 to June 2016.

Starting from morning 9:00 to evening 22:00, more than 13 hours per day, the voice traffic per user value stays above 25 milierlang (merl). 25 merl is the value used in the deployed network in UMTS capacity planning. As we observe in graph (Figure 5-16), the peak traffic per user value is determined 36.26 merl.

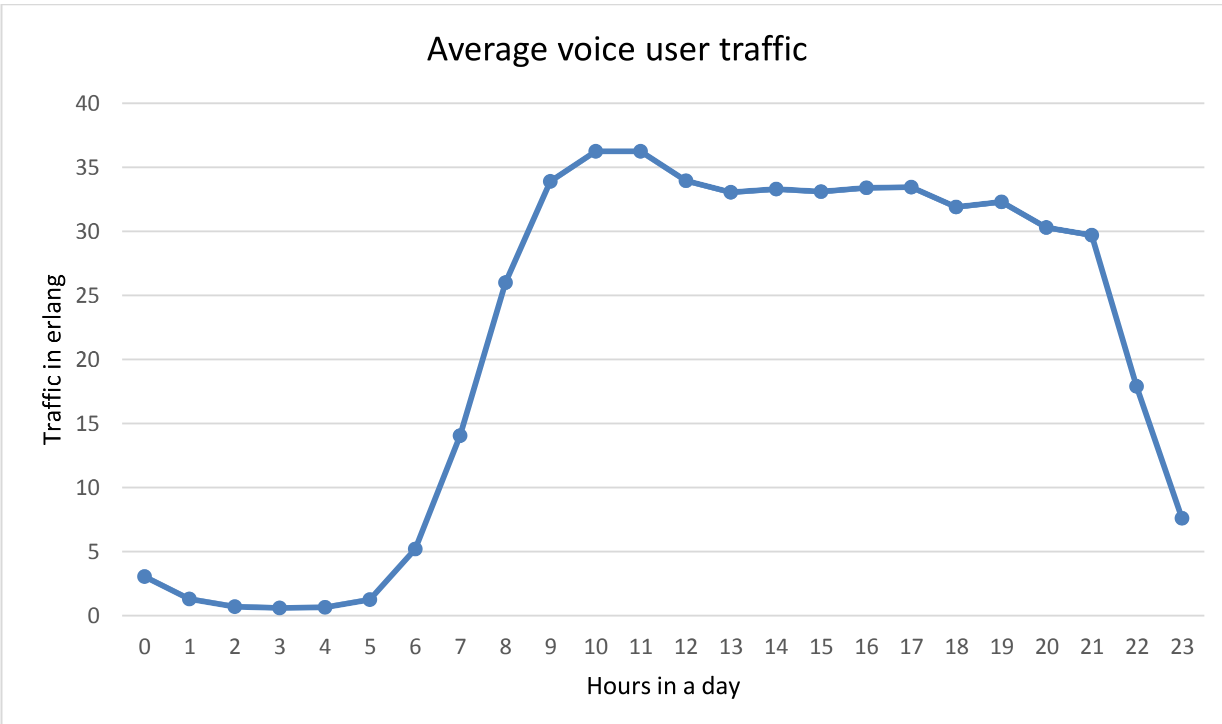

Figure 5-16 Average voice traffic (December 2015 to June 2016).

As Figure 5-17 shows, the peak voice traffic per user value found from the forecasted result has a value more than the deployed user profile value. The same observation has been seen in both prediction time step values, one-step and multi-step. 35.5 merl value is the maximum (peak) value from one step prediction. 33.35 merl and 33.2 merl peak values are the maximum voice traffic per user from multi-step prediction of N = 12 and N = 60 respectively.

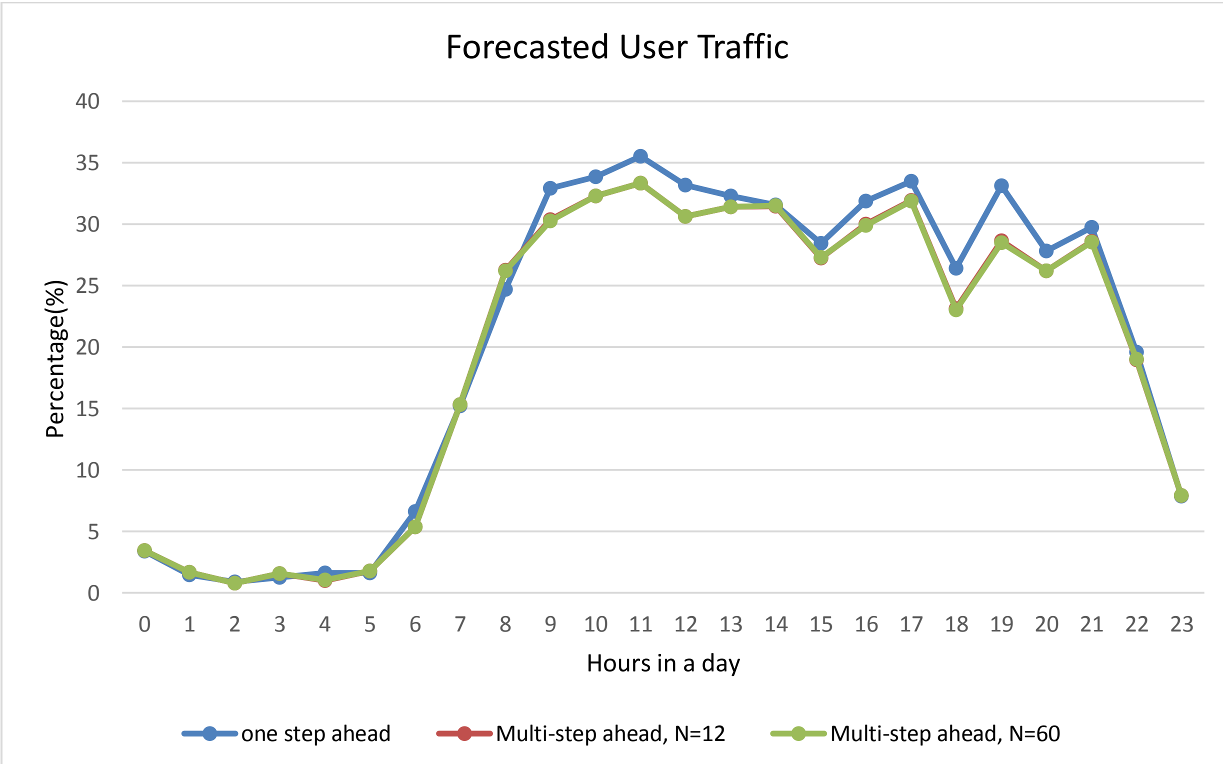

Figure 5-17 One step and multi-step CS traffic per user forecasted average values.

5.6 DATA TRAFFIC PER USER

Similar to daily data traffic pattern observation of the daily packet data traffic, the single user traffic also follows a similar traffic pattern. User's traffic usage increases in all day time hours (from 6:00 until evening). The peak value is occurred in evening before midnight. And as shown in the average packet switch data graph (Figure 5-19), the average peak value occurred at 22:00 (from 21:00 until 22:00).

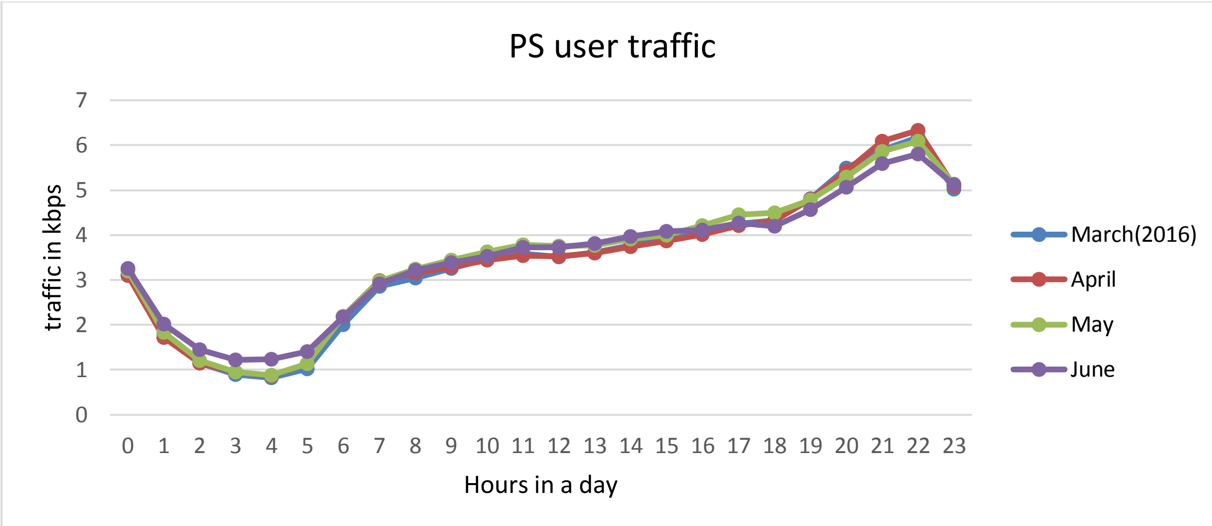

Figure 5-18 PS traffic from March 2016 to June 2016.

Data traffic has an increasing trend in day time and get its peak hour in the evening. This time period is when the majority of data users are online or accessing the data service at the same time. The collected data clearly shows that in the evening time most users' access internet service. This is the time when users settle in home after having completed their day time travel, shopping, dinner and other responsibilities.

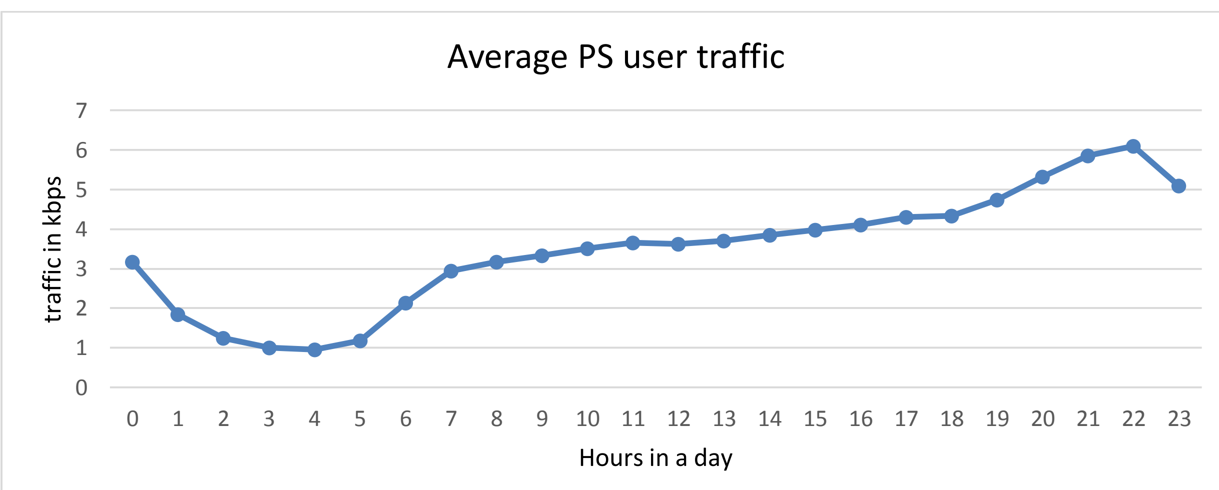

Figure 5-19 Average PS traffic (from March 2016 to June 2016).

The forecasted traffic has similar pattern as the average measurement result (Figure 5.20). 6.1 Kbps is the maximum throughput from the collected data. In the forecasting, 5.78 Kbps is observed in one step prediction and 6.32 Kbps and 6.33 Kbps values for multi-step for N=12 and N=60 respectively.

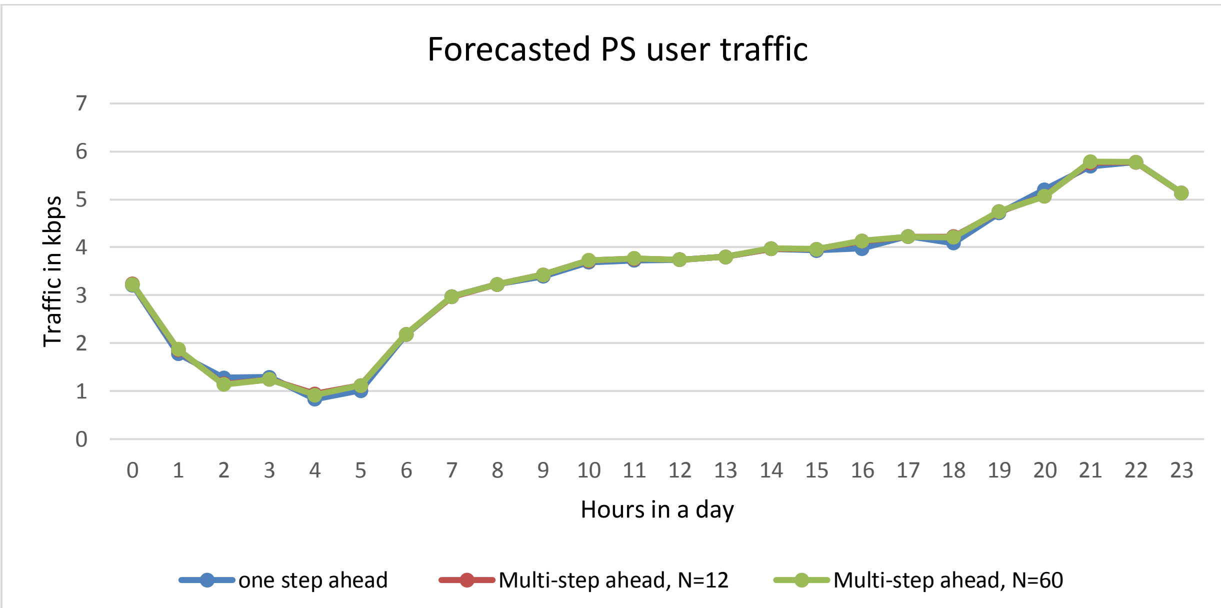

Figure 5-20 One step and multi-step PS traffic per user forecasted average values.

5. 7 DEVELOPED ANALYZER TOOL

To simplify the observation and make analysis on the variations due to input assumption of the traffic model, analyzer tool is prepared by using Microsoft visual basic 2010. This analyzer tool is a flexible methodology that we can use to analyze the capacity analysis result and its input variation effects. By analyzing the result, we can acquire an understanding of how a present system operates, and what would happen if we change the input assumption of the user traffic profile. We can also estimate how a proposed new or expansion system capacity would require to handle the service at busy hour.

In the cell load analyzer tool, the capacity calculation result analysis is performed based on the user traffic profile. Three user traffic profile values are analyzed. The first traffic user profile is the deployed user traffic profile used in the capacity planning calculation. The second traffic profile is obtained from the real time measurement data collected for 14 consecutive months. The third model is the new traffic model determined from the forecasted result.

This tool is based on algorithms described in Chapter 3. The equations from (3.1) to (3.11) are the base for mathematical calculation. We use text box values to represent key numerical measures of the input and output of the system. And we also use formulas, programming statements and others to express mathematical relationships between the inputs and outputs.

Cell load analyzer will calculate the total number of subscribers supported per cell. To make the result very clear, the output result is observed from the number of Node B aspect and display the variation observed in the amount of Node B with its configuration type. From the result, we can conclude whether there is extra Node B or less number of Node B is deployed compared with the deployed capacity planning result. The outcomes from our analyzer show how numerical values for the given variables will determine our capacity and service quality.

As shown in the below figure (Figure 5.21), user traffic parameters are partitioned in three different rectangular areas. The parameter variables are of three types: subscriber related, traffic related and user usage related. Below the input boxes, the calculation output results will be displayed for each equations described in chapter 3. The Node B value, showed in the bottom text box of the analyzer, will help us to compare this thesis result value in business, quality, capacity and other related perspectives views. These values tell the observer the number of Node B used as extra (over the required capacity planning result) or deployed with less amount.

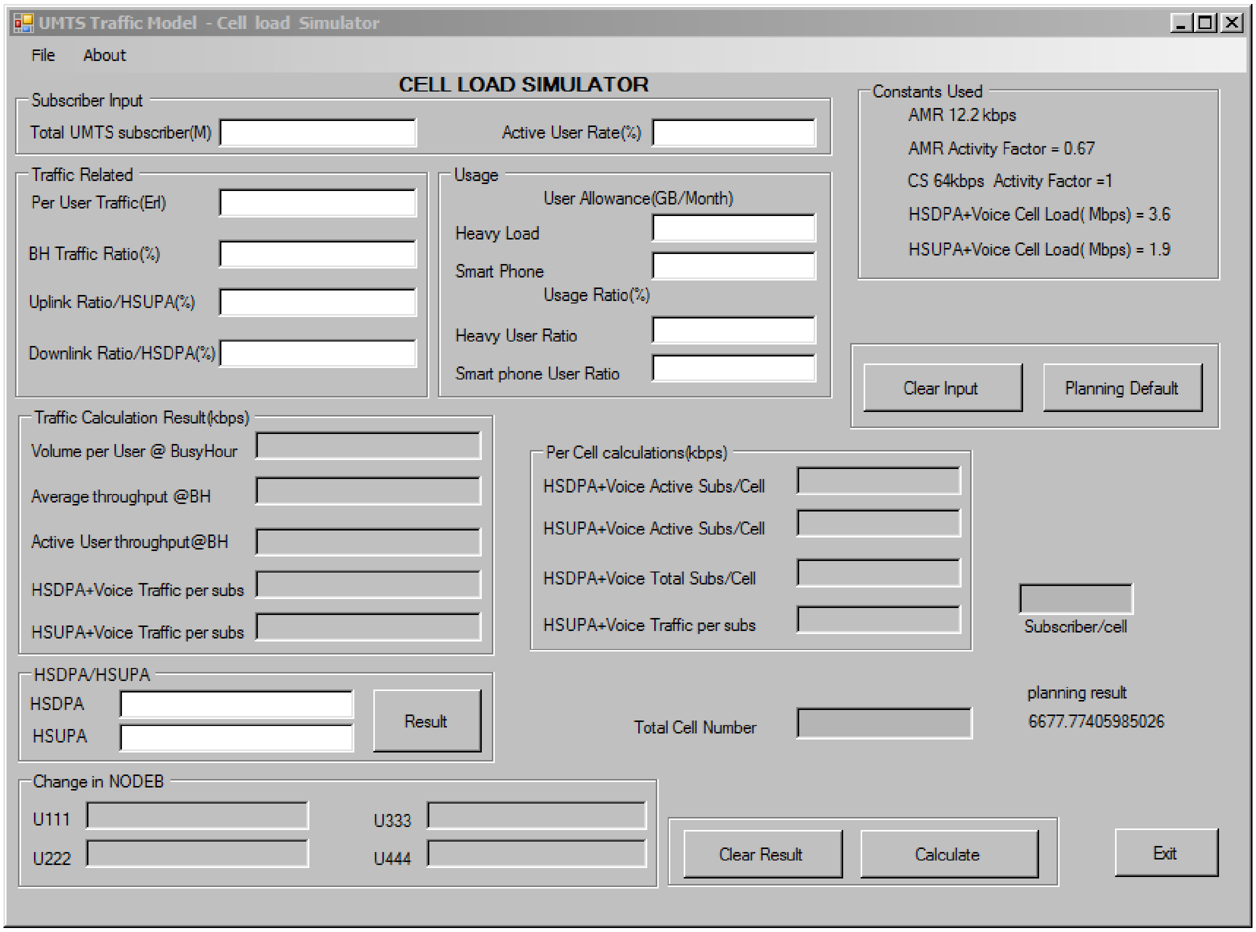

Figure 5-21 Cell load analyzer tool.

5. 8 RESULT FROM THE DEVELOPED ANALYZER TOOL

As it discussed in the first Chapter, the aim of this thesis is to determine and forecast user traffic related measurements to set the traffic related inputs in capacity analysis. The result of our analyzer is based on the four traffic related input parameters.

- ✓ Traffic per user in Erlang
- ✓ Busy hour traffic ratio
- ✓ Uplink ratio
- ✓ And downlink ratio

As indicated in the limitation section of the first Chapter, the total number of subscribers, active subscriber ratio, data usage per month and user usage ratio values are used directly from the deployed traffic model.

The forecasted user traffic profile values are classified in three types,

- ✓ Result from one step ahead forecasting.
- ✓ Result from multi-step ahead forecasting for one year (N=12 months).
- ✓ Result from multi-step ahead forecasting for five years (N=60 months).

Table 5.1 describes the traffic model input parameters used in the simulator. So, based on the average input parameters, the following results are observed and determined.

- ✓ Based on the deployed input parameter, the cell load result is 224 subscriber per cell.
- ✓ By taking the average of the collected real time performance data, the obtained result is 239 subscribers per cell.
- ✓ From one step ahead forecasting, the result is 238 subscribers per cell.
- ✓ From the multi-step forecasting result, the average of the next 12 months gives 226 subscribers per cell and 60 months gives 228 subscriber per cell.

Load per cell result determines the total amount of cell numbers. This can be observed in the result more clearly by taking the number of cells as a comparison value. The total number of cells and subscribe per cell result values of the output result is summarized in Table 5.2.

Table 5-1 Traffic model input parameters.

Parameters		Traffic model				
		Deployed	System measure ment collected data	Forecasted result		
				one step ahead	Multi-step ahead	
					N=12 months (1year)	N=60 months (5 year)
Total subscribers		1502592				
Active subscriber's ratio (%)		70	70	70	70	70
Usage/month/ user(GB)	heavy user	10	10	10	10	10
	Smartphone	1	1	1	1	1
Usage ratio	heavy user ratio	35	35	35	35	35
	Smart user ratio	65	65	65	65	65
Voice traffic per user (in Erlang)		**0.025**	**0.03626**	**0.0355**	**0.03335**	**0.0332**
Busy hour traffic ratio (%)		**10**	**8.08**	**7.87**	**8.46**	**8.47**
Uplink ratio (%)		**30**	**19.17**	**16.31**	**17.86**	**18.82**
Downlink ratio (%)		**70**	**80.83**	**83.69**	**82.14**	**81.18**

Table 5-2 Cell load analyzer result.

Parameters	Traffic model				
	Deployed	System measurement collected data	Forecasted result		
			one step ahead	Multi-step ahead	
				N=12 months (1year)	N=60 months (5 year)
Total cell number	6678	6275	6324	6658	6589
Number of subscriber per cell	224	239	238	226	228

6. CONCLUSION AND FUTURE WORK

6.1 CONCLUSIONS

Capacity analysis for UMTS cellular systems plays a vital role in network dimensioning and planning. Together with coverage planning and quality of service, the forecasted result of this work can be used in UMTS system planning to set hard limits on the maximum number of users that can be served in a single cell. The forecast result will help the network operator (ethio telecom) to estimate the cost of equipment and the network load.

The forecasting model used in this thesis (ANN) is suitable for predicting time series data learning from the given data without any additional information that can bring more confusion than prediction effect. The model ability to learn using example, training data, makes it very flexible and powerful. It is also very well suited for real time traffic prediction system because of its fast response and computational times.

This work shows the way of predicting, modifying and determining the basic UMTS capacity planning parameters which have significant impact. This helps to determine the traffic ahead of time. In the forecasted traffic value, parameters which affect capacity and quality of service are determined in simple and usable expression. The operator can use the method and its result for new and expansion project work.

Taking the deployed capacity analysis result as a reference point, this paper reaches a conclusion based on the three traffic model output values and its related business expenses.

- ✓ Real time performance collected data analysis

According to the real time collected data analysis, the number of subscriber supported per cell has higher value than the deployed planned parameter. 239 subscribers can be supported per single cell or carrier. Based on the analysis, 403 cells are excess or extra resources. Based on this, the number of cells (equivalently, number of Node B) are more than the required capacity planning result.

- ✓ Multi-step forecasting result, N= 12 months

The number of subscribers served in a single cell with in the coming one year is forecasted as 226 subscribers per cell. Based on this result, slightly higher number of users is supported than the deployed result. An increase in subscriber number per cell will decrease the total number of cells required. Even if the traffic is showing an increasing trend, additional 20 cells are still observed as excess for the coming one year forecasted period.

- ✓ Multi-step forecasting result, N= 60 months

The traffic usage has an increasing trend as the number of months are increased. Observing the traffic five years ahead will tell us that the total subscriber supported per cell is predicted to be 228 subscribers. Since an increase in cell load capacity is observed, the load of the traffic will not force the network to add extra cell numbers, because still 89 cells are observed as excess number. The holding capacity of the network will get efficient if the number of cells remain the same as of the deployed result provided that total number of subscriber is unaltered.

- ✓ CAPEX and OPEX business expenses

To visualize the business expenditure property, it will be better to change the result in the form of mobile equipment hardware. Excess or less number of cells can be converted to their equivalent number of Node B. The result obtained from multi-step forecasting result for N= 60 months can be taken as sample to demonstrate CAPEX and

OPEX business expenses. The Node B configuration vary based on the carrier configuration. Uxxx (UMTS 3 sector x number of carriers) configuration is the common type configuration implemented in the deployed system. U111 needs three carriers or cells, U222 is to mean each sector has 2 carriers, which needs a total of 6 carriers or cells. And similarly for U333 and U444, U333 configured with 9 carriers (cells) and U444 configured with 12 carriers (cells). Based on this configuration 89 excess cells have equivalent meaning of 30 Node B with U111 or 15 Node B with U222 configuration or 10 Node B with U333 or 8 Node B with U444 cell or carrier configuration. In all these scenarios, capital expenditures (CAPEX) and operating expenses (OPEX) will increase.

6.2 FUTURE WORK

This thesis studies the capacity planning analysis with possibilities of traffic parameters from live network history data. Parameters which are not included in this study due to lack of time and measurement data are left for future work.

- ✓ As this thesis tries to use data mining on the measured traffic data, the study also invites other researchers to use data mining on parameters which are used directly from the operator forecasting result. Data mining holds great potential to improve accuracy in planning and uses analytics to identify best practices. So, researchers are invited to use data mining approaches in parameters like customer's traffic usage from smart phone and dongle device. Smart phone and dongle device data usage ratio is used directly from the operator forecasted result. But as a future work, it is advised to get the result from the real time call detail record (CDR) measurements.
- ✓ To decide the exact number of cells in UMTS system, total subscriber number and user traffic usage are heavily coupled in the capacity analysis number of cells

determination. Total number of forecasted subscriber and active subscriber ratio values, which have a major role in varying the result, are directly used from the company forecasted result. By taking the subscriber number forecasting process as one limitation factor to this work, other researchers can continue by including their own total customer forecast result in their further investigation to come up with a better capacity analysis result.

- ✓ The maximum data that can be collected during the work of this thesis is 14 consecutive months. In future, other researcher can proceed by taking long period real time measurement data.
- ✓ This thesis uses ANN for forecasting user traffic data. Readers of this thesis are invited to do the forecasting process with other forecasting techniques or methods to have an alternative in capacity analysis and dimension result.

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