DEMAND-BASED CAPACITY PLANNING

OF

MOBILE CELLULAR NETWORKS IN AFRICA

By

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A thesis submitted in partial fulfilment of the requirements for the degree

MAGISTER TECHNOLOGIAE: ELECTRICAL ENGINEERING

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ABSTRACT

Accurate traffic demand estimation is critical in ensuring that optimal communication resources are allocated to handle available traffic load with minimum system congestion and effective utilisation of expensive resources. To achieve such an optimum design, capacity planning must be based on actual traffic demand available in the intended areas of coverage.

In this study, an accurate traffic demand estimation tool, T-DET, was designed and implemented in Rwanda, Africa. Based on the *terminal mobility model*, the tool estimated available traffic demand in three planning scenarios: *Suburban Commercial*, *Suburban Residential*, and *Rural* scenarios and subsequently establishes optimum capacity configuration. Results of the tool indicated that traffic demand can be accurately estimated in all cases resulting in high resource utilisation and better performance. High utilisation of resources was obtained, with 95.57% and 85.36 % utilisation value for suburban residential and rural scenarios respectively. There was also notable reduction in cell congestion from 8% to 0.7% in suburban commercial area, 14% to 1.6 in suburban residential area.

The tool could be further upgraded to undertake traffic forecasting given population growth estimates in given areas of interest.

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DECLARATION

I declare that this thesis is my own work and has not been submitted in any form to any other institution for another degree. Information derived from published or unpublished work has been fully acknowledged and a list of such references has been provided.

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David K Kanamugire

DEDICATION

This work is dedicated to those champions who embrace and harness technology to address social challenges in the world for the benefit of all mankind.

ACKNOWLEDGEMENT

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CHAPTER 1

INTRODUCTION

1.1. Introduction

To stay profitable and competitive in a deregulated mobile cellular market in Africa which is characterised by low income subscriber base and a severe lack of telecom engineering expertise, network operators require specialised skills and sophisticated network design tools to undertake accurate mobile network capacity planning and implementation.

Such design should be based on realistic traffic demand available in the intended areas of coverage to ensure maximum utilisation of scarce resources, minimisation of operating costs and improving high Quality of Service. To address these constraints, the Telecommunication Development Sector (ITU-D), the development branch of International Telecommunications Union (ITU), has proposed teletraffic engineering methods for cost-effective design and operation of telecommunication networks. The role of teletraffic engineering is mainly to *"adjust the amount of equipment so that variations in the subscriber demand can be satisfied without noticeable inconvenience while the costs of installation are minimized, the equipment must be used as efficiently as possible"* [14].

Due to highly volatile space and time traffic variations inherent in mobile networks, the use of fixed-line teletraffic models in dimensioning of mobile networks have been severely challenged [39].

While the stationary nature of the fixed line calls offered a stable operational environment and predictable quality of service, resulting in the design of high quality networks, the volatility of mobile calls have resulted in uneven, unpredictable and usually low quality of service [39]. The traffic variations have resulted in system congestion and associated lost calls and in extreme cases, very low resource utilization figures.

Intense research has been underway in attempting to develop teletraffic models and tools that could address the challenges introduced by mobility and its associated volatility and bring the capacity planning of mobile networks to that of the well known and predictable fixed-line Public Switched Telephone Networks [12]. In an attempt to provide a stable and predictable operational environment, mobile network operators and equipment vendors have had to resort to *ad hoc* planning methods. These have included building networks with large spare capacity so as to meet predicted intensive subscriber growth and avoid long site acquisition delays. Equipment vendors on the other hand, have provided various capacity relief schemes like:

a) Dynamic Channel Allocation (DCA), where all channels are kept in a central pool and assigned dynamically to new calls as they arrive in the system [50].
b) Cell load sharing, where the traffic load is spread to neighbouring cells with less traffic load
c) Queuing, in which calls are not immediately dropped if a channel is not available but wait a short duration, often resulting in call setup delays

All these features are aimed at exploiting the *temporarily unused resources* caused by short-term traffic fluctuations. These methods have adverse implications to the overall cost and quality of the network.

In this study, a new teletraffic engineering method of determining teletraffic demand based on user demographics and land usage is evaluated. The resulting traffic demand per service area is used for allocation of resources and eventual equipment design and configuration based on established demand. The benefits of accurate demand estimation enables mobile network operators to minimise operating costs, minimise system congestion while maximising resource utilisation.

1.2 Problem statement

Mobile network operators in Africa are faced with challenges of achieving cost effective and high quality network design. Capacity planning is still based on *ad hoc* methods of resource allocation, complimented with continued monitoring and tuning system performance in the field as the network evolves. This has led to two major challenges in designing of cost effective and high quality networks. *Firstly*, allocation of large amount of resources in low traffic environment leads to low resource utilization, which leads to wastage of expensive radio transceiver units.

Secondly, allocating too few resources in high traffic areas leads to system congestion which ultimately results in low call setup success rates (increases dropped call rate). This leads to lost revenue for an operator and dissatisfaction by subscribers. Subscriber dissatisfaction leads to increase in churn rates (*subscribers switch to network operator that offers better quality).*

In this study, we address these challenges by designing and implementing an accurate traffic demand estimation tool, *T-DET,* which uses local demographic data to estimate available traffic demand in a specific service area of interest. Equipped with accurate traffic demand information, system resources can be allocated effectively, and an optimum cell capacity configuration determined.

1.3 Purpose and objectives of the study

The purpose of this study was to design and implement an accurate traffic demand estimation tool to aid in optimum capacity planning of mobile cellular network in Rwanda. From such an optimum design, the following benefits were realised:

i. Maximise resource utilisation.

ii. Improve Quality of Service.

iii. Gain pre-operational information about expected traffic and hence expected revenue.

1.4 Delimitations of the study

This study aims at designing and implementing a traffic demand estimation tool that can use readily available demographic and geographic data in a given service area of a single site within a cellular network. The tool does not intend to replace existing network design tools or the role of a radio network planning engineers in capacity and performance monitoring as the network evolves from the original design conditions but to offer an easy to use tool in the early phase of capacity planning. Network performance monitoring is a continuous activity as networks continue to change to meet subscriber activities and demographic patterns.

To minimise the computational complexity of time varying traffic fluctuations due to numerous and often irregular user mobility patterns, the study is limited to the busiest hour traffic, assuming a static population of users that are camped on a target cell irrespective of the traffic source or destination. Since the tool can not accommodate all possible variations of a particular planning environment, the first order estimates will require manual capturing of key input parameters.

This tool establishes traffic demand based on currently demographic data or available future projections in demographics. It does not undertake to forecast socio-economic conditions which would determine future traffic demand in a particular area but utilizes already published data to calculate the future traffic demand. Furthermore, the model estimates traffic demand for a site to be planned and does not take into considerations all factors that could change the traffic load within the network like busy events in neighboring sites, load sharing due to neighbor site congestion and others.

1.5 Outline of the dissertation

This study discusses the use of demographics and geographic data in estimating spatial traffic demand traffic in a service area of a mobile cellular network.

Chapter 1 discusses problems associated with inaccuracy in determining the required capacity under-dimensioning which leads to a higher blocking rate and congestion of network resources, various approaches that have been attempted by mobile operators are discussed and a novel methodology of allocating resources based on established demand is introduced.

Chapter 2 reviews existing teletraffic engineering methods in general and challenges associated with these methods in accurately estimating the expected traffic and the resulting demand for resources in mobile cellular networks.

Chapter 3 discusses the demand based approach of estimating traffic demand methods. The traffic estimation tool designed to implement the chosen method is presented in detail. Various tools used in gathering the data used in this approach are presented and the design of a validation tool that was developed for implementing the methodology is discussed in detail. Various simulation scenarios are presented in this chapter.

Chapter 4 details the development of the demand estimation tool, *T-DET,* with illustrations of the design and coding of the key tool modules that compute traffic demand.

Chapter 5 presents the results of the validation tool obtained in the three planning scenarios.

*Chapter 6 a*nalyses results obtained in chapter 5.Based on these results, practical cell capacity configuration is established. Utilisation figures are also calculated based on capacity demand.

Chapter 7 draws conclusions based on the results obtained and recommends further areas for research, which would further improve the accuracy of the estimation method and render the tool used in commercial network planning scenarios.

C H A P T E R 2

LITERATURE REVIEW OF DEMAND-BASED PLANNING METHODS

2.1 Introduction

The purpose of this chapter is to introduce the reader to some theoretical background in the field of teletraffic engineering and its applications in capacity planning of telecommunications networks. This is necessary for developing an understanding of planning constraints encountered in the design, resource allocation and optimal configuration of cellular networks. Analytical models that are based on the traditional Erlang theory are presented and their limitations in estimating traffic demand for cellular networks which support user mobility are presented. *A novel model, "the terminal mobility model",* which is based on spatial geographic models and was implemented for the context of Rwanda, is presented in detail.

2.2 Review of capacity planning methods and models

As indicated in Chapter 1, "*Adequate models do not exist for mobile networks that support cellular and Personal Communications Services (PCS)*", that support user and terminal mobility. This is mainly due to the fact that commercial roll out of mobile networks has surpassed standardisation work for teletraffic models specific to mobile cellular networks [13]. To achieve an optimal network configuration, network operators require accurate knowledge of available traffic load in a given service area of a cellular network to ensure deployment of optimum resources to handle the traffic load. This is needed to maximise system resource utilisation, minimise congestion and reduce unnecessary capacity upgrade/downgrade cycles caused by inaccuracies in accurately estimating traffic demand, several approaches have been considered.

Several approaches for estimating traffic demand in a given service area in a network are presented in the literature. The most commonly used of these methods are:

a. Analytical methods based on adapted Erlang models based on fixed telephony
b. Traffic Simulation models
c. Measurements-based approach

Analytical models, based on traditional Erlang theory and Poisson distributions have been challenged due to the mobility nature of mobile calls [36]. Simulation models that attempt to model mobility patterns of mobile users as they roam within a coverage area of a cellular network have proven to be numerically accurate. The difficulty in calculating location probabilities of mobile users and establishing required input parameters have however rendered their use in practical planning scenarios very limited [36]. A more reliable approach of accurately estimating traffic demand has been measurement based simulation [26]. This approach uses traffic measurement records extracted from exchanges and then use this for forecasting. While this is the most reliable way of actual traffic demand establishment, it cannot be used in pre-operational planning scenarios where no such measurements yet exist.

A new approach to estimating traffic demand has been proposed by the ITU-T in its ITU-T Recommendation E.760: *Terminal mobility modeling for Public Land Mobile Networks (PLMN)*. This Geographic traffic model uses easily available demographic and land usage data to estimate prevailing spatial traffic demand in a service area of a cellular network [14].

2.3 The call set-up and arrival process

To introduce the principle of capacity planning and develop sufficient theoretical understanding of the subject as used in telecommunications capacity planning, the classical *teletraffic theory* is briefly reviewed. The concept of traffic intensity, traffic flow rate, quality of service (QoS) and grade of service (GoS) were introduced to precede the methodology employed in the next chapter. The review of the Erlang-B formula, which has been the cornerstone of telecommunications networks capacity planning and dimensioning is discussed. Teletraffic engineering aims at designing telecommunication systems as cost effectively as possible within a predefined grade of service.

The purpose of teletraffic engineering, which is the cornerstone of cost-effective telecommunication networks design and operation, is to *"adjust the amount of equipment so that variations in the subscriber demand can be satisfied without noticeable inconvenience while the costs of installation are minimized. The equipment must be used as efficiently as possible"* [14].

To model traffic demand in a telecommunication networks, traffic processes are defined and the subscriber behaviour is then characterized. The call arrival rates and the rate at which they are processed give an indication of the existing traffic intensity. The factors contributing to traffic intensity in a cellular network include the number of calls arriving at that cell or an exchange and their average call duration.

Figure 2.1 below indicates this relationship between the call set-up processes and call Mean Holding Time (MHT), which is the average duration of each call in seconds.

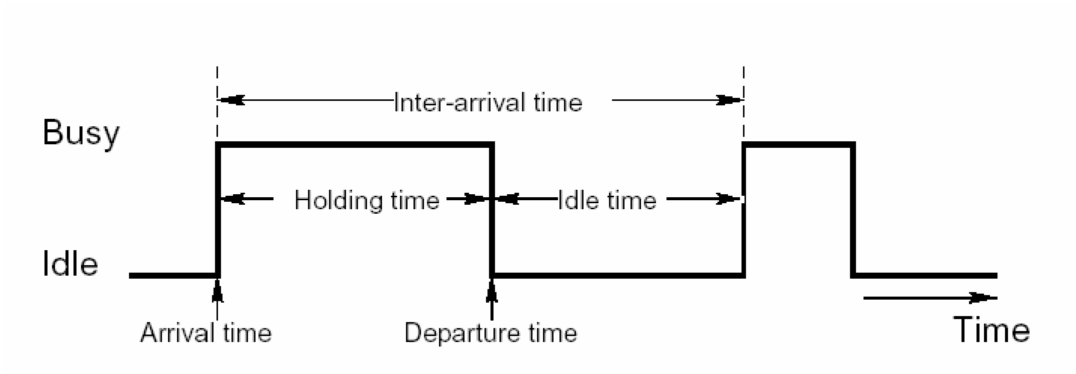

Figure 2.1: Call setup process

It can then be seen here that the traffic intensity at a point in a network like a cell, switching centre or a base station controller, is related to the use of radio channels. This intensity is also directly proportional to the number of phone calls and the average duration of those calls. Traffic generated per subscriber, ρ', in a mobile network is defined as:

$$\rho' = \lambda' \times 1/\mu \text{ Erlang} \qquad (2.1)$$

Where λ' is the number of calls a user makes in a given period, and $1/\mu$ is the average call duration in seconds. This equation indicates how long on average a user occupies a radio channel, within a certain amount of time (seconds). Assuming that a user makes an average of 3 phone calls an hour, with each call lasting 1.5 minutes, the amount of traffic generated per subscriber (ρ') would then be $\rho' = 3/60 \times 1.5 = 75$ mE.

From the above example, it can be deduced that if users call ***n*** times an hour, with each call lasting for ***m*** seconds, the traffic intensity generated ***ρ'***, is given by the equation

$$\rho' = (n \times m)/3600 \text{ E} \qquad (2.2)$$

2.4 The busy hour and blocking concept

Since it would be impractical to dimension a network for all possible traffic variations for all times, network dimensioning is carried out for the peak time called, the *busy hour*. The busy hour is defined as "*The continuous 1-hour period lying wholly in the time interval concerned for which the traffic or the number of call attempts is greatest*". This is used to estimate demand at the highest traffic peak [15]. The figure below indicates the busy hour variation for a residential area, with peak traffic occurring at point A, at 20:00H

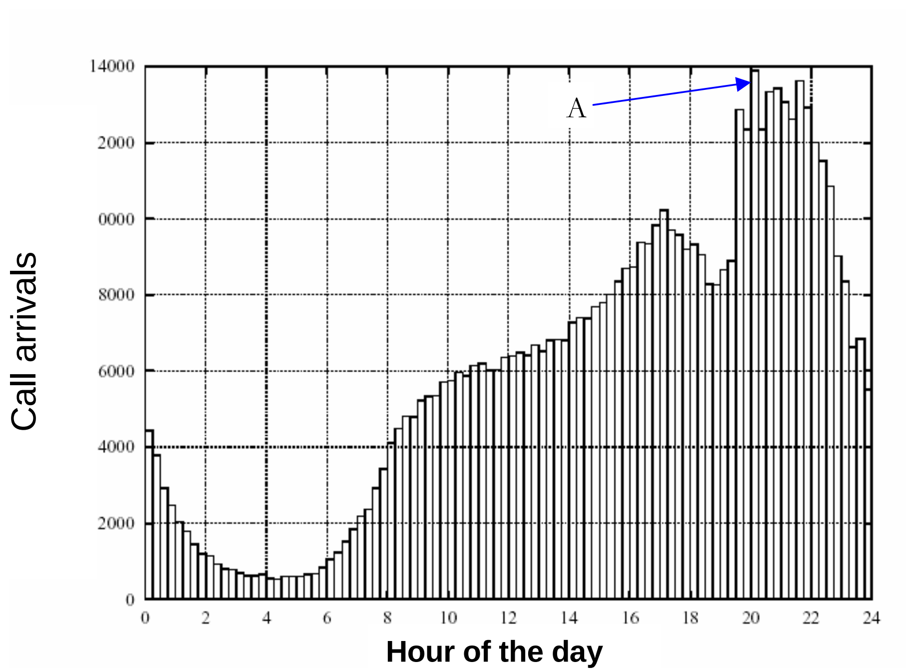

Figure 2.2: The Busy Hour concept

The highest traffic does not occur at the same time every day and longer time variations are necessary. The average busy hour traffic concept is hence used here. Also daily, weekly and yearly variations are used. The dimensioning should therefore cater for the traffic of the busiest hour of the busiest day of the week and the highest seasonal annual period.

Since it is also not feasible to install an infinite amount of resources to allow all subscribers to speak at once, but rather allow some degree of inconvenience based on the probability that a portion of subscribers might not use the resources during the busy hour, the *blocking concept* is introduced. If the subscriber can not make a call due to insufficient resources, the call is either blocked or put in queue to wait for any available resource to be released. This causes congestion in cells, and mobile systems attempt a retry to establish a call from the queue.

2.5 Teletraffic models

Teletraffic models are the foundation for establishing the call patterns and the subsequent traffic demand. The next sections describe some of the commonly used teletraffic models used in capacity planning of telecommunications networks.

2.5.1 The queuing call model

In attempting to model calls in mobile systems, a network is viewed as a queuing system, characterised by [46].

i. A certain number customers queuing for service.

ii. A number of servers.

iii. A number of waiting rooms.

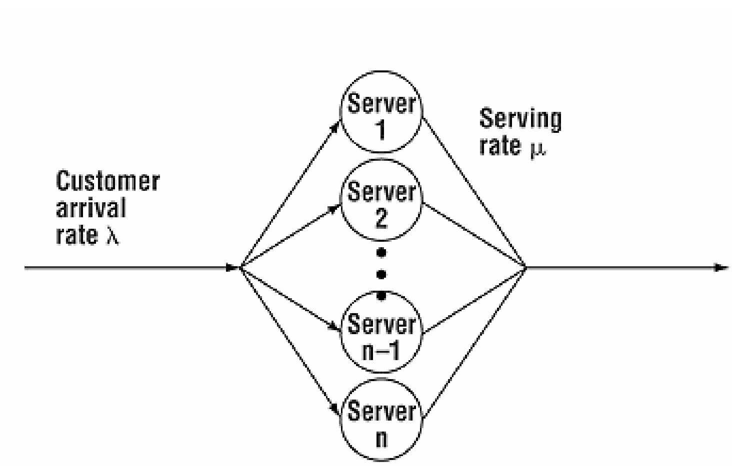

Figure 2.3: The memory-less queuing model of n servers

The serving behaviour of the system is determined by the customer arrival and serving behaviour of the system.

In the queuing model, the rate of arrival behaviour is then modelled as the probability distribution of customer arrivals indicating the frequency of arrival of customers to a service centre. Serving behaviour is modelled as the probability distribution of a service. It is important to note that the arrival and serving behaviour would take more forms with different arrival and serving patterns. Queuing theory uses different models to determine how communication resources will be allocated. The simplest form of queuing is known as *M/M/1/x* model. The first *M*, which represents the arrival distribution, is memory-less. The arrival of one customer is independent of other customers. This is generally true for any wireless communication system. The second *M*, representing the serving distribution, also is memory-less. The serving time of a customer is independent of all other customers.

The *1* means there is only one server in a system, while *x* indicates that there are an infinite number of waiting rooms in the queuing system.

The probability of this system having k customers (P_k) is defined as

$$P_k = (1 - \rho)\rho^k \tag{2.3}$$

Where $\rho = \lambda/\mu'$ is the total arrival rate, and $1/\mu$ is the mean serving time

The traffic intensity then becomes *E= (N.h)/3600,* where *N* is the total number of calls arriving in one hour and *h* is the average call duration.

Traffic intensity is then calculated for the number of busy channels at a given instant in time. If the time duration of calls and the number of channels occupied are known, the intensity *Y (T)* can be calculated as:

$$Y(T) = \frac{1}{T}\int_0^T n(t)dt \tag{2.4}$$

Where *n (t)* is the number of busy channels at time *t*.

The *traffic carried, (Ac)* is then the amount of traffic carried by a pool of resources during the time interval *T*.

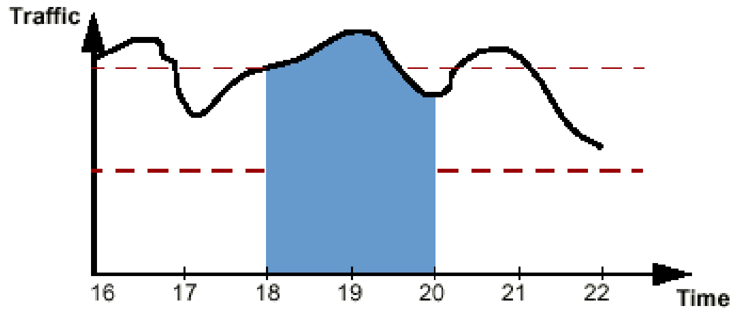

Figure 2.4: Traffic volume

The offered traffic, A_0, is a theoretical value that indicates the amount of traffic that would be carried if no calls are lost due to lack of capacity [14]. It is calculated as the product of call intensity, λ and the mean call holding time, s.

$$A_0 = \lambda .s \qquad (2.5)$$

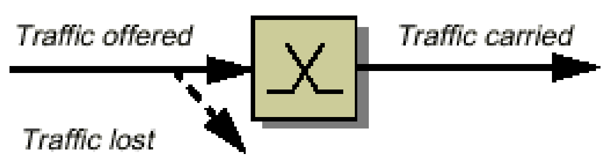

Figure 2.5: The traffic carried

The traffic carried is the difference between the theoretical traffic offered and the traffic lost due to unavailable resources as indicated in the figure above.

2.5.2 The Erlang Traffic Model

Erlang traffic models, a century old method of estimating demand for communication resources has been reliably and accurately used to dimension and cost effectively operate fixed line telecommunication networks. These models formed the basis of capacity and quality planning of telecommunications networks and have even found their entry into new technologies despite severe limitations to changing operational requirements.

The stationary nature of the fixed line calls offered a stable operational environment and predictable quality of service that resulted in design of high quality networks.

The Erlang models assume that a call arriving at the system is accepted for a service if a free channel exists otherwise it is lost. This is called the Erlang's Loss Model (LM) also called the Lost Calls Cleared (LCC) Model [14]. The model assumes that calls arrive at random without any relationship between any successive calls.

The model also assumes that the number of available channels is infinite and the call holding times are exponentially distributed with intensity, μ corresponding to a mean value of $\frac{1}{\mu}$ and the arrival rate of λ.The definition of offered traffic then becomes:

$$A=\lambda \frac{1}{\mu}=\frac{\lambda}{\mu} \tag{2.6}$$

State probabilities are then used to evaluate the offered traffic for the number of busy channels, *(i=0, 1, 2, 3….).*

The Poisson distribution probability is defined by the equation

$$p(i) = \frac{\frac{A^{i}}{i!}}{\sum_{v=0}^{n} \frac{A}{v!}}, \leq i \leq n. \qquad (2.7)$$

The Erlang-B formula computes the probability that all the available n channels that are busy at a random point in time is equal to the time average

$$E(A) = p(n) = \frac{\frac{A^n}{n!}}{1 + A + \frac{A^2}{2!} + \ldots + \frac{A^n}{n!}} \qquad (2.8)$$

Knowing the state probabilities as given in the equation 2.8, the carried traffic is calculated as:

$$Y = A.\ \{1 - E\ (A)\} \qquad (2.9)$$

The lost traffic A_l is given by A-Y as indicated in figure 2.3 and traffic congestion is calculated from equation 2.10 below.

$$E(A) = \frac{A - Y}{A} \qquad (2.10)$$

The resource utilization can be derived by assuming that all channels carry the same amount of traffic (which is a pure characteristic of voice networks, but invalid for data networks with burst IP traffic). The random hunting principle assumes that all channels carry the same amount of traffic and utilization is given as

$$a = \frac{Y}{N} = \frac{A\{1 - E(A)\}}{n} \qquad (2.11)$$

The equation indicates that we obtain the highest resource utilization for maximum congestion E (A). As earlier indicated Erlang theory was developed primarily for fixed-line telephone networks that were predominantly voice based with known network attachment points and fixed bandwidth per call.

Since cellular networks are characterised by high user mobility and volatile radio environment, methods of establishing traffic demand in mobile networks differs greatly from the well known methods used in fixed line telephone network. [24].

Firstly, there isn't an infinite amount of customers in a cell of a mobile network.

Secondly, congestion caused by multiple call attempts must be considered. This is typically so in mobile networks for subscribers to reattempt to call after initial call setup failure in an attempt to seize a traffic channel. This further congests the network. As the cell traffic approaches the congestion limit, the blocking probability increases at a much faster rate than the theoretical value. In a real-life scenario, the arrival of customers (when a user makes a phone call) is highly correlated to the customers blocked by the system (when a user gets the busy tone).

Thirdly, for mobile networks, arrival and serving assumptions are determined by other factors like pricing terms, off-peak call rates, income of the subscriber, and existence of other means of communication. As an example, subscribers might use different networks that offer cheap call rates at specific times or based on income household income levels. They may also use alternative means of communications like fixed line telephones.

Finally, marketing strategies and pricing schemes greatly affect traffic behaviour. When an operator reduces the tariff on mobile calls, traffic increases greatly. This would require the addition of more radio channels to the network. As a result, traffic intensity needs to be revised from time to time in order to reflect real-life scenarios.

2.5.3 The mobility traffic model

High spatial and time mobility of mobile users have been the key differentiator in developing teletraffic engineering models for mobile networks, "s*ince Erlang models have failed to accommodate mobility related traffic demand estimation due to spatial and temporal volatility of mobile terminal" [*44]. Mobility models have been suggested to model user mobility and characterise the resulting traffic demand for mobile cellular networks. Based on road transportation theory, these models assume uniform a unidirectional traffic flow, regular road networks with known vehicular and pedestrian movement patterns and other hard to find parameters like the average speed of users, the length and pattern of the streets and the average number of cell-boundary crossings per hour.

All these variables have impact on the call arrival rate and the call handover rate, the cell residence time (the time a call stays on a cell before being handed over to its neighbour as a result of the user movement) [44].

Figure 2.6 is a model of estimating the traffic demand in an oval shaped cell with the indicated street pattern by estimating car crossing rate for an area of size A. The crossing rate is calculated as:

$$\lambda_{car} = \sum_{i=1}^{n} \sum_{j=1}^{l_{nb}(i)} \rho_{i,j} \quad \text{(Cars/hour)} \tag{2.12}$$

Where n is the number of streets crossing the border, *lnb(i)* is the number of lanes in street

i(i=1, 2, 3…n) and $\rho_{i,j}$ is the car crossing rate for lane j of street *i*.

The pedestrian crossing rate can be estimated by the same analogy.

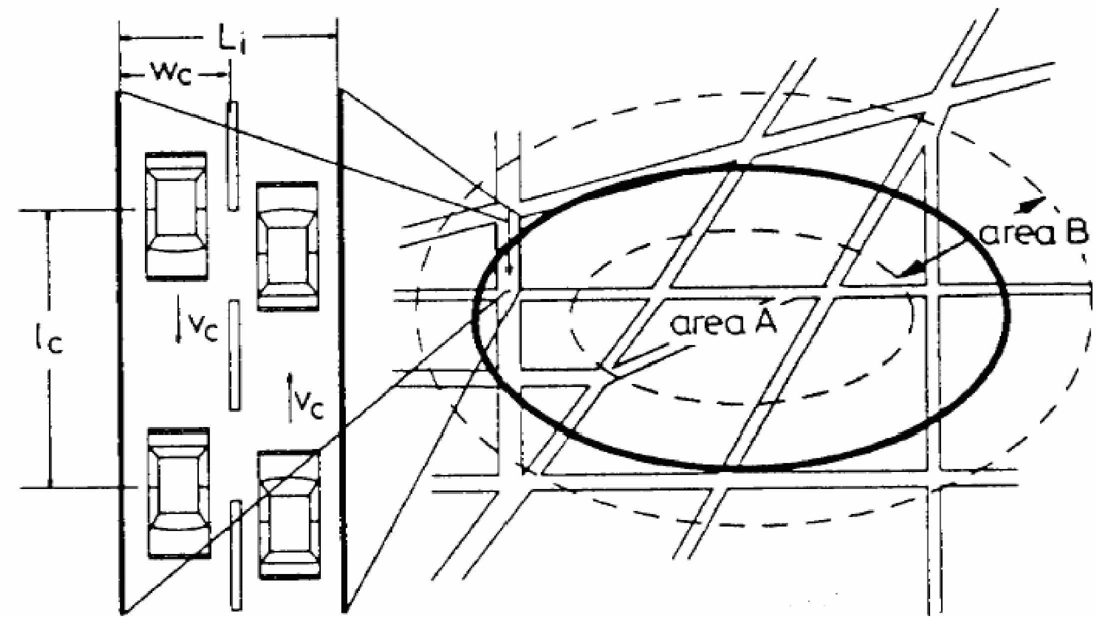

Figure 2.6: A model for evaluating car crossing rate in cell

The application of these models in real life network planning is very limited since the model depends on very many factors such as the average vehicles speed, distance between any two moving cars and more, as indicated in Figure 2.6 [44].

These models, though analytically accurate for regular shaped road networks, have failed to model areas where road networks are irregular with high variations in travel speeds, variations between vehicular and pedestrian users, and also the rate at which people join or leave these highways. Their computational complexity and the randomness of mobile users have rendered their use limited in practical planning environments.

The fluid model assumes human movement as the flow of a fluid, where the amount of traffic flowing out of a service area is proportional to the population density within the area [44]. Given a circular region with a population density of ρ, an average user travel velocity of $\boldsymbol{v}$, and region circumference of $\boldsymbol{L}$, the average number of site crossings per unit time $\boldsymbol{N}$ is given by:

$$N = \frac{\rho \pi L v}{\pi} \tag{2.13}$$

This model is appropriate for well planned streets (called the Manhattan type of streets) but becomes inaccurate as the layout of streets becomes geometrically irregular. This is because of the assumption of uniform movement with respect to the boundary does not hold for irregular layouts [24].

The major limitation of the fluid model is that it describes aggregate traffic using average user velocity, which is hard to obtain in real planning environments.

Another attempt to model human movement within a service area is by using the *Markovian model,* also known as the random-walk model [24]. The model assumes that the mobile subscriber will either remain within a region or move to an adjacent region according to a transition probability distribution. This model is fairly accurate for pedestrian subscribers but is inaccurate in case of vehicular traffic where the subscribers flow is determined by road conditions and street pattern.

The gravity model, based on Newton's laws of gravity is another approach used to estimate traffic demand based on *human mobility patterns* within a given service area .It estimates traffic flow in a service area by predicting user movement patterns from one area to another [47]

In its simplest form, the gravity model estimates the amount of traffic, $T_{i,\,j,}$ moving from region *i* to region *j* as:

$$T_{i,j} = K_{i,j} P_i P_j \tag{2.14}$$

where P_i is the population in region *i*, and $\{K_{i,\,j}\}$ are parameters that have to be calculated for all possible regions pairs (*i, j*). The different variations of this model usually have to do with the functional form of $K_{i,\,j}$.

The advantage of the gravity model is that frequently visited locations can be easily established for demand estimation purposes [32]. The main difficulty with applying the gravity model is that many parameters have to be calculated and it is therefore hard to model geography with many regions [5].

2.6 The terminal call model

Due to the computational complexity of mobility models presented in previous sections, which result from difficulty in either obtaining input data or calculating positional probabilities of mobile users within the area and failure of Erlang models to accurately estimate demand for networks with user and terminal mobility, efforts have been underway to use geographic models which are appealing in their use due to easily available input variables and reduction in computational complexity.

Terminal mobility traffic modeling is intended to characterize the mobile user traffic demand associated with mobile services within a service area of the cellular network.

In geographic traffic models, the traffic demand in an area is estimated from geographic and demographic characteristics of the service area.

In the *geographic traffic model,* the required traffic intensity $E_{geo}{}^{(t)}(x,y)$ is the aggregation of traffic originating from various contributing factors [49].

This intensity can be estimated by the equation:

$$E_{geo}^{(t)}(x,y) = \sum_{all\_factors\,i} n_i . \delta^t(x,y) \qquad (2.15)$$

where η_i the traffic is generated by factor, i in an arbitrary area element of unit size measured in Erlang per unit area, and $\delta_i^{(t)}(x,y)$ is the assertion operator:

$$\delta_i^{(t)}(x,y) = \begin{cases} 0: factor\_i\_not\_valid\_at\_location\_(x,y) \\ 1: factor\_i\_valid\_at\_location\_(x,y) \end{cases} \qquad (2.16)$$

In an attempt to evaluate the value $E_{geo}^{(t)}(x,y)$, the traffic generated by the contributing factor *i,* is expressed as:

$$\eta_i = \text{a}.\, b^{x_i} \qquad (2.17)$$

Where η_i is the traffic normalisation factor, ***a*** is a constant, and ***b*** is the base exponential function. The values of base index ***a***, and ***b*** are normally assumed and given a constant value of 10. The above equation is, however, complex for actual traffic demand computation as it relies heavily on the assumed value.

To reduce the complexity, a normalization constraint is introduced that is a function of the total traffic intensity and the surface areas of the service area

$$\frac{E_{total}}{A_{service\_area} / a_{unit\_element}} = \sum_{all\_factors\_i} \eta_i \qquad (2.18)$$

where $A_{service\_area}$ is the size of the service area and $a_{unit\_element}$, is the size of the unit area element and E_{total} is the total teletraffic in this region.

The geographic traffic model calculates the traffic intensity function $E^{(t)}(x,y)$, which describes the offered teletraffic as seen by a fixed network element like a base station in a unit area at location *(x, y)* and at time instant *t.* The coordinates (x, y) of the grid are integer numbers and the function can be derived from the location probability of the mobiles. If the probability of the mobile location $P_{loc}^{(t)}(\chi,\psi)$ can be known, then the model calculate the average number of mobile stations in the location bound by coordinates (x, y) at time *t* as:

$$N^{(t)}(x,y) = \int_{x}^{x+\Delta x} \int_{y}^{y+\Delta y} P^{t}{}_{loc}(x,\psi)dy.dx \qquad (2.19)$$

Where $N^{(t)}(x,y)$ is the number of mobiles camping at location (x, y). The size of the unit area is given as:

$$\text{A}=\Delta x \,.\, \Delta y \qquad (2.20)$$

In actual planning environment, it is not possible to calculate the location probability, $p_{loc}^{(t)}(\chi,\psi)$ of a mobile within a cell. This makes the model almost unusable and either call detail records or statistical traffic measurements used for estimating the traffic intensity [49]. One of the most appealing geographic models, the *terminal mobility traffic model*, proposed in March, 2000 by ITU-T in its recommendation E.760 involves estimating pre-operational spatial traffic demand in a service area by using geographical data [39].

This model assumes that despite the time dependent traffic variations, the traffic demand in a cell, regardless of the source or origin of the traffic being carried in the target cell, is consistent for daily and seasonal busy-hour variations. By exploiting this busy hour traffic predictability, mobility complexities and the resulting handover traffic (to and away from the target cell) are eliminated and only the actual traffic carried is considered.

This simplification has made the model realistic in actual planning scenarios and can further be tuned to give even better results once the traffic data is available for calibrating of the input variables. In the equation $E_{geo}{}^{(t)}(x, y)$, indicates that the time function accounts for temporal variation in traffic intensity within the element (x, y).

Since the networks are dimensioned for maximum load during the busy hour, the time index *t* can be dropped and the equation reduced to a stationary geographic traffic model. The model starts by creating the best server of the target cell for which traffic demand is to be estimated. The area is divided into grids of equal sizes. By knowing the population residing in that grid and the statistical traffic generated per subscriber, the traffic demand can be estimated.

This figure is then summed up for all the grids that fall within the service area. By mapping the best server region into the population density map, a first order estimation of the traffic demand per sector can be realized as indicated in figure 2.7 below.

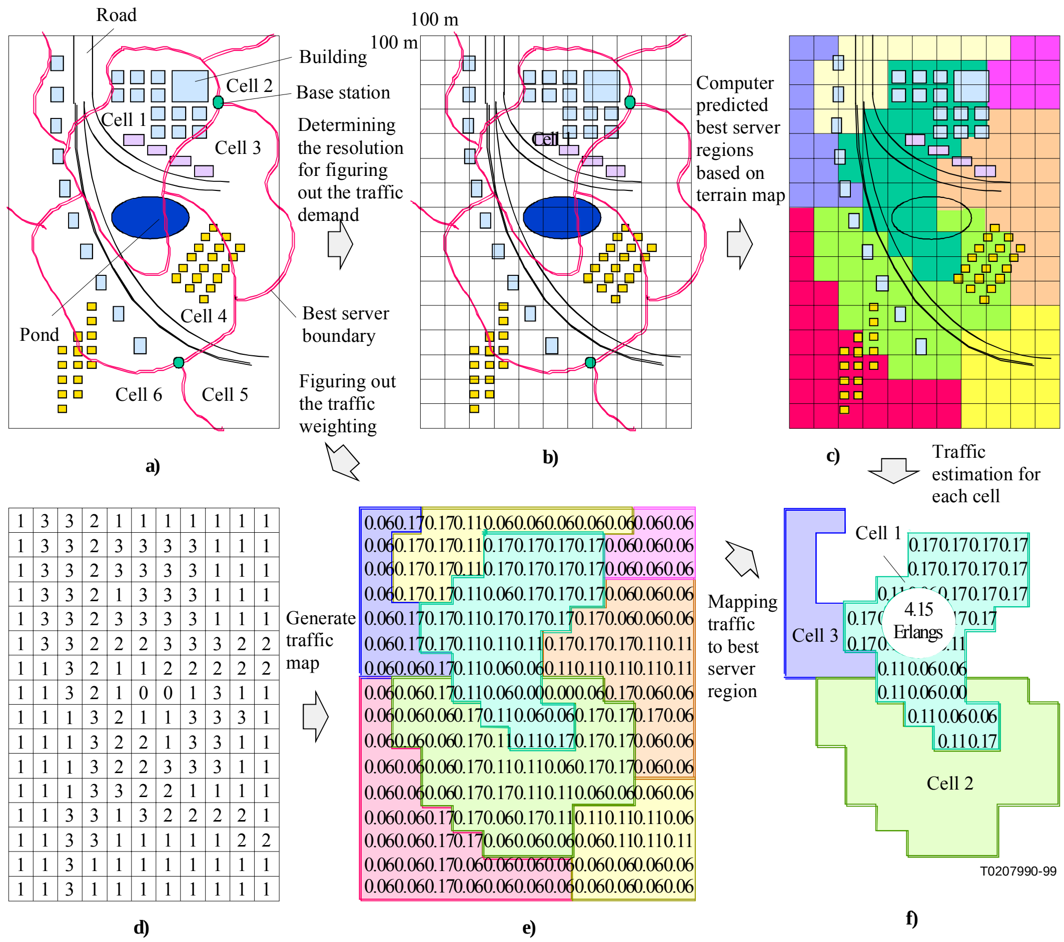

Figure 2.7: Estimating demand from population distribution and coverage area

The procedure for traffic demand estimation using the terminal mobility model as indicated in Figure 2.7 above is as follows:

Step 1) The best server regions associated with the base station sites is noted.

Step 2) The map of the area is divided into equal grids and superimposed to the service area.

Step 3) The contour of each best service region is approximated by the sequence of the closest sides of the elemental areas. In this way, a discretization of the best server region is realized.

Step 4) Each grid on the map is assigned a weighting factor depending on the *geographical features* of the underlying portion of service area.

Step 5) Traffic demand is allocated to each grid on the map. The details of the computations are as follows:

i) Normalization factors associated with each elemental area in the ideal grid are computed based on the related weightings given as in Step d). The normalization factors are used to apportion the traffic offered in the service area to the best service regions and, ultimately, to the base station sites;

ii) A first order traffic demand estimation per grid area is computed by multiplying the traffic offered per user by the user density in a grid area (the user density in that grid is obtained by dividing the total population by the surface of the service area, and multiplying by the service penetration rate);

iii) The first order traffic demand per grid obtained in under ii) above is multiplied by the related normalization factor. This yields the traffic demand associated with each grid.

Step 6) The products in iii) under Step e) related to the grids comprising the same best server region are summed up: this gives the traffic demand associated with each base site.

2.7 Conclusion

This chapter reviewed theoretical teletraffic models used in traffic demand estimation process. Application of these theoretical teletraffic models in practical mobile cellular planning environment is limited by their computational complexity, arising from the difficulty in establishing accurate location of mobile users within a certain geographic area.

The strong dependence of these *theoretical teletraffic models* (including variants of mobility and gravity models) on the geometrical accuracy of road networks, and the associated difficulty in obtaining necessary input variables like *average vehicular speed*, *user crossing rates*, *duration* which users stay on a specific unidirectional road and other hard to obtain modeling parameters, makes its application in network capacity planning not feasible.

In Rwanda, where this study was conducted, the road network infrastructure is either poorly planned or simply inexistent that input variables for these models are unavailable.

Furthermore, the impact of pedestrian users, who roam within a service area, not necessarily following road network but rather use pathways to congregate around food market areas (a typical economic activity in developing countries), makes mobility models inapplicable as they do not account for this proportion of subscribers, who contribute significant traffic volume.

Due to the limitations posed by the theoretical teletraffic models discussed in this chapter and the difficulty in obtaining the necessary input data, we choose to implement and evaluate the ITU proposed *Demand Based Model* based on its appropriateness in addressing critical limitations of other models

CHAPTER 3

THE TRAFFIC ESTIMATION PROCESS

3.1 Introduction to traffic estimation process

The traffic estimation method used in this study is based on the terminal mobility traffic model presented in chapter 2. This model is an adapted geographic traffic model that uses demographic and land usage data in a particular local environment to estimate *spatial traffic demand* in Erlangs/km^2 of a service area of a cellular network. The amount of required resources to meet the desired capacity and subsequent cell configuration is obtained by mapping resulting traffic demand to traffic channels, resulting in capacity configuration of the cell concerned.

In order to handle the calculation, the tool calculates the demand in two steps. The first step assumes uniform land usage and hence the computation results in uniform traffic distribution per unit grid on a map of the area, neglecting the impact of underlying land usage. The second part assigns weights to each grid based on the underlying land feature.

To undertake the study, the areas of interest were first characterised based on various traffic patterns to reduce the number of scenarios. The areas under study were broadly classified in three classes based on their *traffic patterns* and land usage features as *Suburban Commercial, Suburban Residential* and *Rural* areas. These are typical of the planning environment in Rwanda. Due to the low density of very tall buildings and nearby few busy streets per unit area typical of large cities, no area fitted the urban classification. One method of classification was on *the time of occurrence* of the *busy-hour.*

The busy-hour have been defined earlier as the *time of the day when the cell experiences the highest traffic volume* and occurs in different parts of the network at different times and can give an indication of traffic flow pattern between the planning areas. This is due to the fact that subscribers exhibit a known and predictable movement pattern as they commute between home (residential cells) and work (commercial cells) resulting in similar traffic flow pattern. This subscriber commuting, results in a similar traffic flow pattern resulting in a fixed busy hour for the same day of the week [5].

Figure 3.1 below indicates hourly traffic profiles for the three planning scenarios in Kigali. These measurements resulted from querying the Statistical and Traffic Measurements Database (STS) on the concerned BSC using SQL Queries as indicated in Appendix C.

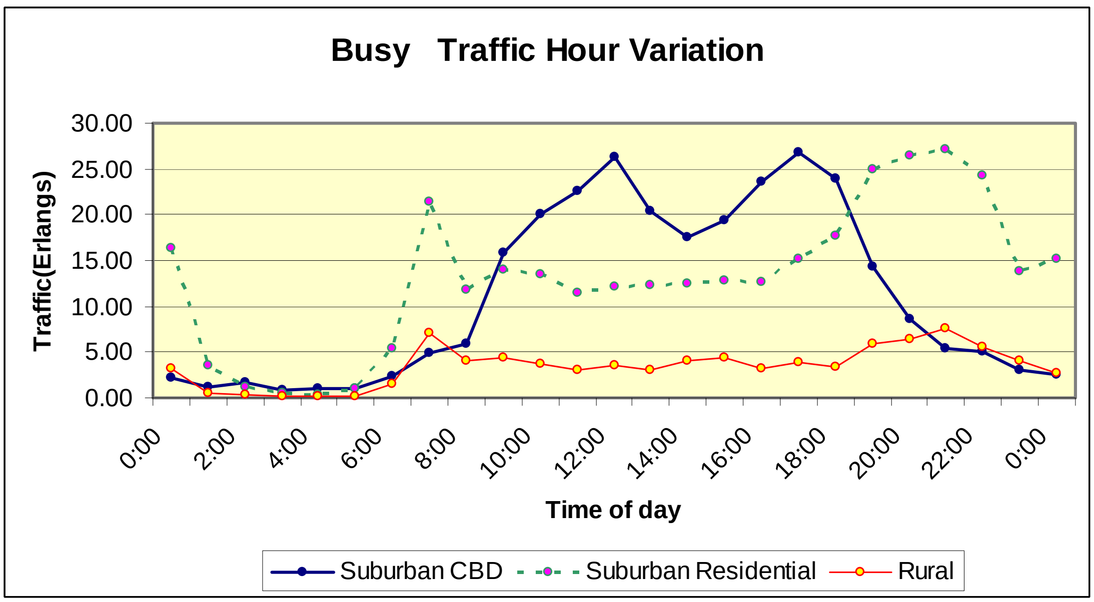

Figure 3.1: Hourly traffic variation

From figure 3.1 above, it has been shown that:

a) In the suburban commercial area, two peaks exist at 13:00 H and 17:00 H, with busy-hour occurring at 13:00 H.

b) The suburban residential area also exhibits two peak times at 07:00 and 21:00 H, with the busiest hour occurring at 21:00 hours.

c) The rural areas exhibit low busy hour traffic volumes, typically less than 10 Erlang for the highest peak period, with no noticeable busy-hour traffic peak in most cases.

d) The areas are typically in the countryside. They are characterised by low count of business centres and are relatively far from main highways and commercial centres in areas extending to a radius of greater than 20 km from the nearest commercial centre and high way road.

The classical classification of areas based purely on population density is not valid in Rwanda due to lack of clear difference in population densities between rural and urban areas. The current residential plan called *Midugudu*, similar to townships in South African context implied that some rural areas exhibited high population densities comparable to suburban environments.

3.2 Best server creation

A *best server area* is taken as that area within cell coverage, where a mobile will receive the *strongest signal* from that planned base station, even though the signal from other base stations may still be adequate for communications. In this study, a best server area was done using propagation tool asset. The area where a strongest signal was received (areas receiving signal strength greater or equal to -75 dBm, depending on penetration requirements like in-building or outdoor) are established and signal level boundaries drawn around these areas. The covered by these cell boundaries is then calculated based on preloaded maps in ASSET and is given as the size of the coverage area for which capacity must be planned. It should be noted that the primary planning phase in to ensure that sufficient signal exists in that particular area.

Figure 3.2 below indicates the areas that meet necessary signal strength requirements. The red areas exhibit signal strengths of greater or equal to -75 dBm and are sufficient for high concentration commercial in-building coverage. The best server coverage map indicates signal strength variations corresponding to minimum requirements for a specific coverage colour scales from Orange (-81 dBm), Yellow (-85 dBm), Green (-93 dBm), Blue (-96 dBm). Signal strengths less than -110 dBm indicate areas where there is no signal coverage and are therefore excluded in coverage area measurements by the propagation tool ASSET.

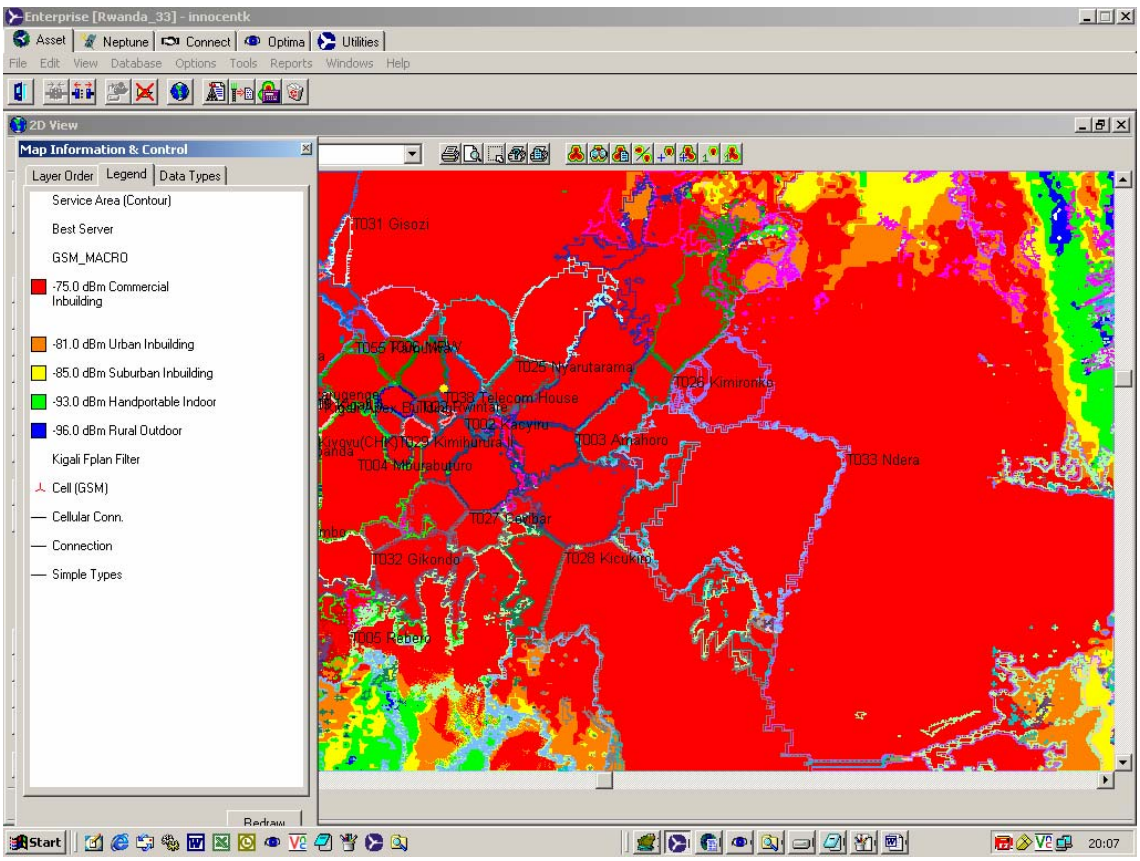

Figure 3.2: Generation of Best-Server coverage array

Once the best server (receive signal level) condition has been achieved, contours are drawn around each cell and the enclosed area is then noted as indicated in figure 3.3.

Once the areas that have sufficient signal coverage have been established in the best server creation as indicated in Fig. 3.2 above, contours are drawn around these areas as indicated in Figure 3.3 below, to separate them from neighbouring cells. A coverage contour indicates the cell boundaries and is also used in handover parameter adjustments during later stages of network optimisation.

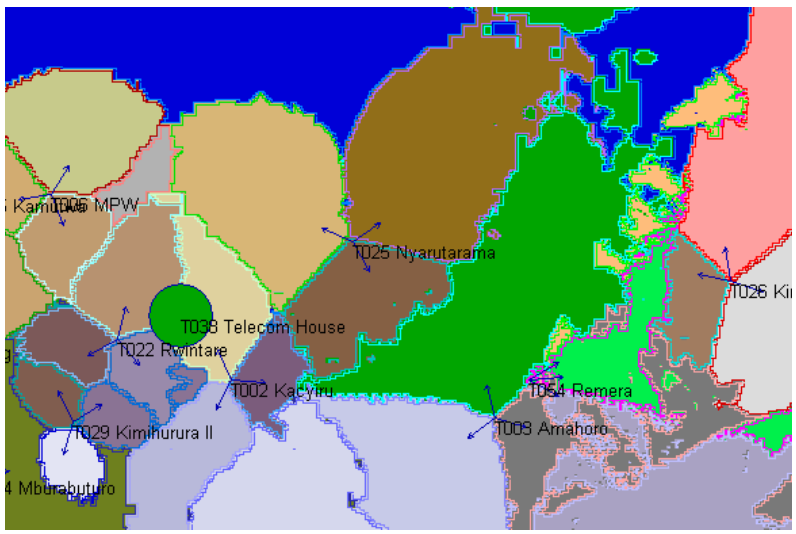

Figure 3.3: The service Area of target cell

ASSET propagation tool calculates the coverage areas for the three planning scenarios as 2.88, 3.08 and 23.67 km^2 for suburban commercial, suburban residential and rural areas respectively. After generating the best server, ASSET generates an excel file that indicates the coverage areas of the desired sites.

3.3 Service penetration rate

The service penetration rate metric ρ indicates the percentage of the population that possesses mobile phones and are active subscribers. The metric is calculated from the population densities of the area under study together with the number of active subscribers.

The number of potential subscribers residing in a specific area can be obtained from both the marketing data and population distribution statistics It is an indication of mobile density in that area. These variables are market estimates and can only be validated when the site is operational. The Call Detail Records database, CDRLive was used to calculate this figure based on operational sites. Table 3.1 shows the service penetration rates for the three area classes under study. The rural area was characterised by very low penetration rate of ρ=0.0025 corresponding to approximately 3 subscribers per every 1000 inhabitants within the entire service area of a cell.

Area Class	Service Penetration, ρ, (2004)	Subscribers/1000
Suburban Commercial	**0.025**	**25**
Suburban Residential	**0.025**	**25**
Rural	**0.0025**	**2.5**

Table 3.1: Service Penetration Rates

3.4 Population density (*number of inhabitants/km^2*)

The population distribution maps available from rural and urban planning offices contain important information regarding subscriber distribution and potential traffic demand. Combined with historical network statistics, both active and potential subscribers can be established.

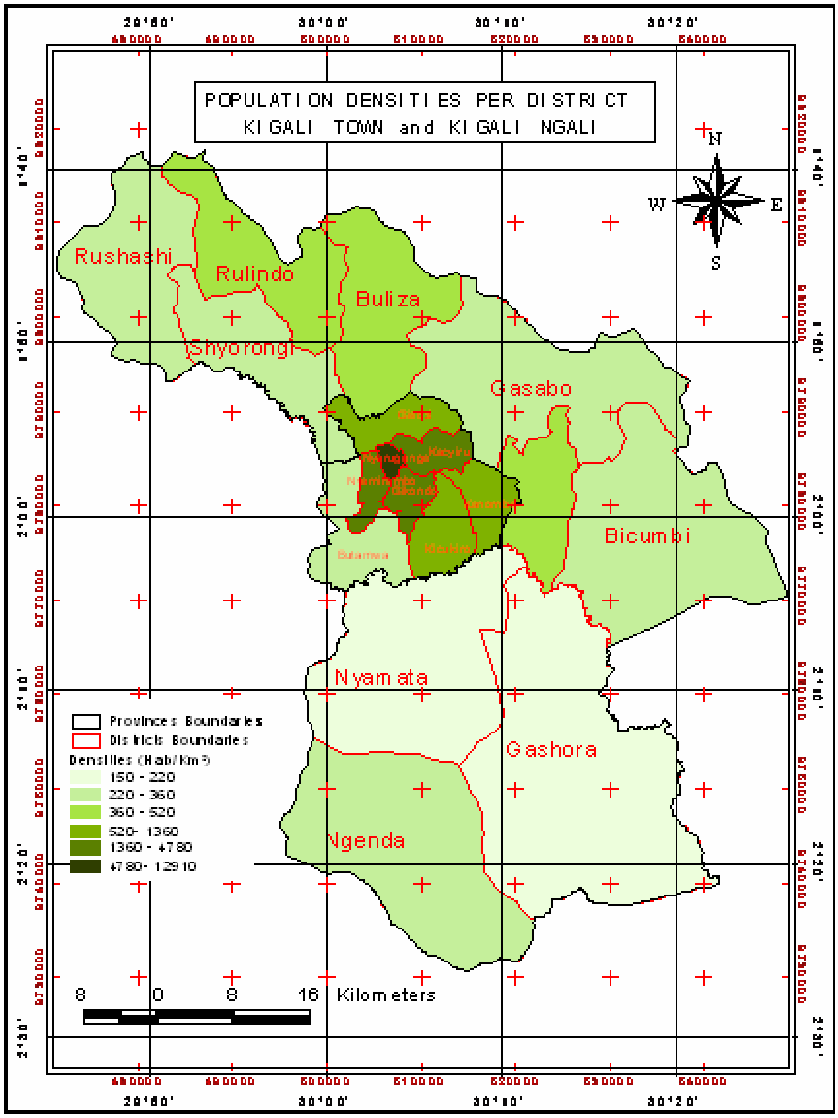

Figure 3.4: Population Distribution map of Kigali area

3.5 Traffic variations

Traffic variations could be derived for busy hour for different time periods: Time of the day, day of the week and seasonal variations. These variations allow dimensioning for the busiest hour of the busiest period (day, week or season)

3.5.1 Busy hour traffic variations

The concept of busy hour classification was introduced at the beginning of chapter 2 with the busy-hour being defined as *the time of the day when the cell experiences the highest traffic volume.*

3.5.2 Day-of-the week variation

Fig. 3.6 indicates traffic variations during the week for the three scenarios under study. Traffic flow between rural and urban areas is nit very much pronounced and weekends generally exhibit low traffic volumes. Friday exhibits the highest traffic, due to activities associated with end of business week in CBD area.

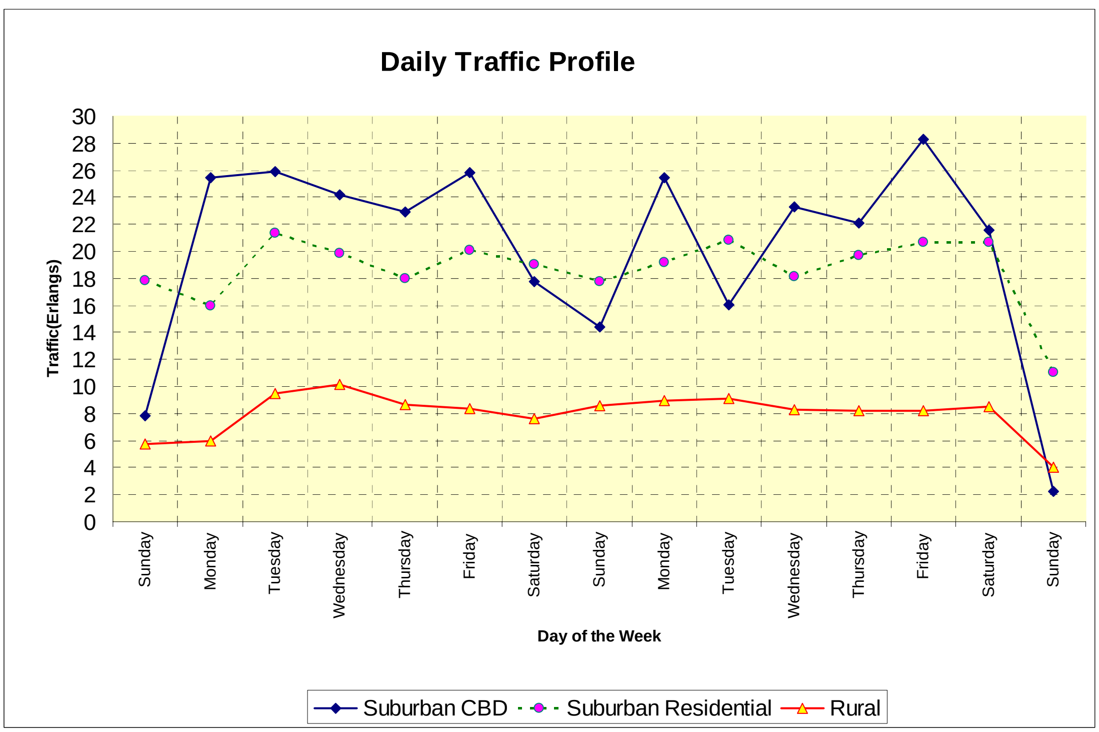

Figure 3.6: Daily traffic variation

3.6 Traffic demand forecasting methodology

The previous sections detailed methods for characterisation and estimation of available traffic demand under present conditions. To enable traffic forecasting, a comprehensive survey of population density growth is necessary to set *differentiated penetration hypotheses* per environments (dense urban, urban, rural) driven by density classes. Such information on the population density distribution over time makes it possible to estimate the geographical distribution of users, and to forecast traffic density at various geographical levels. To narrow down the number of possible factors that would influence traffic forecasts, four major *reference indicators* are proposed to summarize the mobile telecommunication situation and potential development in a specific country and geographic area [53]. These are:

- Income, represented by the GNI (Gross National Income).
- Human Development, represented by the HDI (human development index).
- Technology Affinity, represented by the TAI (technology affinity index).
- Urbanisation.

Using these indicators, international bodies like the International Telecommunications Union, the World Bank and the United Nations Populations Office (UNO), publish data for all the countries in the world. Based on such data, countries are ranked based on their levels of development. These vary from classes A to F, with Class A countries being those that are very developed and industrialized country while class F countries the least developed. Mobile penetration potential is estimated based on these reference indicators per country. Mobile subscriber penetration hypotheses are then drawn using the *S-Curve diffusion model* as indicated in Figure 3.7 [51], [52].

Rwanda, like other least developed economies, is ranked category F in human development indices. Group F countries are the Least Developed Countries (LDCs) characterised by low income, low Human Development Index and/or technologically marginalized [53], [54].

This category exhibits the highest communications growth potential due to lack of existing telecommunications services, while some western developed countries have already reached very high penetration rates of about 90% (Scandinavian countries). Figure 3.7 indicates the development of the S-curve diffusion model for forecasting penetration of mobile services in a given environment. The input to the mode is a set of base data like population distribution, historical penetration rates and reference development indicators per country. Based on this model, areas that have historically had low penetration will exhibit highest growth rate before reaching saturation point.

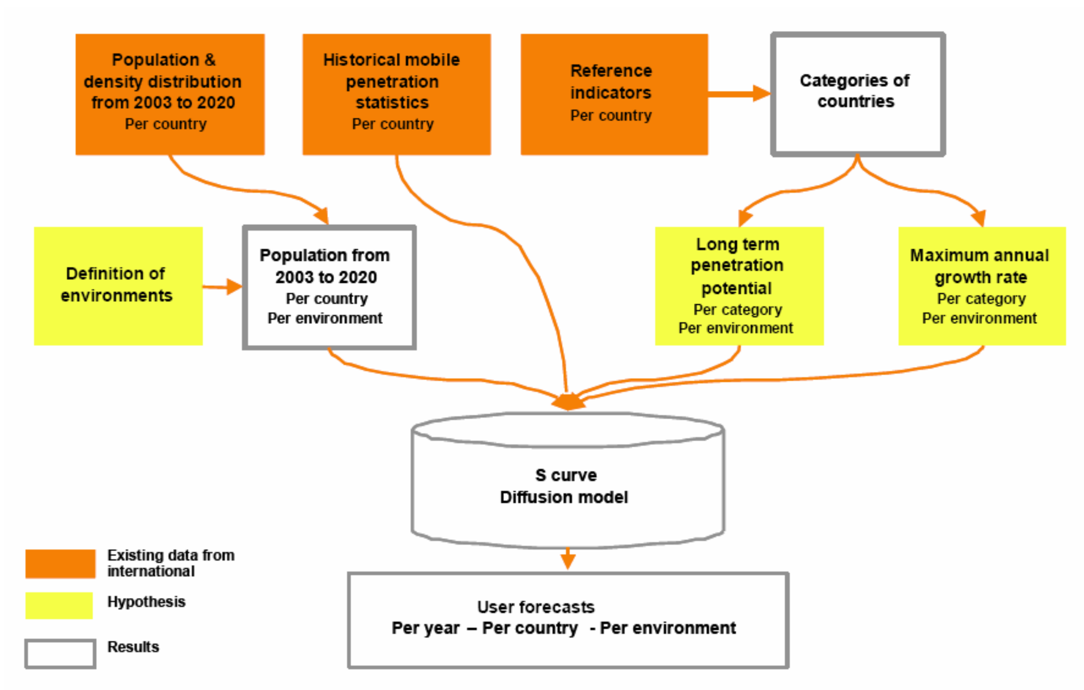

Figure 3.7: Mobile penetration forecast methodology

The penetration of mobile services in a specific country is defined by the *s-curve equation* below. *Max_speed* indicates the highest attainable penetration rate, while the *Max_penetration* indicates the highest possible penetration attainable within a specific country (for example, it is assumed that not every human being can use a phone due to age restrictions) [54].This value is assumed to be between 80 and 90% of the population.

$$Penetration(t) = Max\_Penetration.\frac{1}{1+\exp(-4\frac{Max\_speed}{Max\_Penetration}(t-t_0))} \quad (3.1)$$

Where t_0 is the starting year of projection.

Figure 3.8 indicates penetration rate variation over time, indicating minimum growth in subscriber acquisitions after attaining the penetration of 55%.

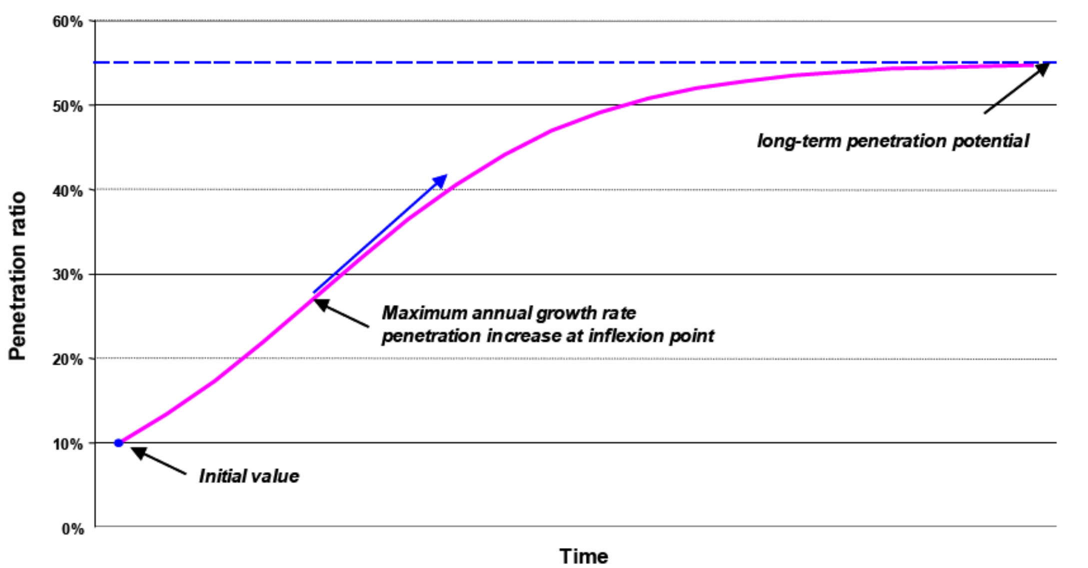

Figure 3.8: An Example of Penetration Evolution Model

3.7 Conclusion

This chapter presented the traffic estimation process for the evaluation of traffic demand available in a service area. The methods of forecasting traffic demand given service penetration rate was also presented. A software tool for estimating the demand is developed in the next chapter.

CHAPTER 4

THE DEVELOPMENT OF TRAFFIC DEMAND ESTIMATION TOOL

4.1 Introduction

The design of the traffic demand estimation tool (T-DET) is based on the previously described ITU-T *terminal mobility traffic model*. The tool enables demand based system engineering by introducing an accurate spatial traffic model that uses publicly available geographic and demographic data to produce spatial traffic demand in a service area of a cellular network. This model relates factors like population density, service penetration rate in a given service area.

The tool was designed in Visual Basic. The calibration database was implemented in Access. The main features of the tool are:

i) The data capture fields.

ii) Traffic demand estimation module.

iii) Traffic Map generation and display module.

iv) Tool Calibration using traffic measurements database.

The tool design and estimation process followed the following stages:

i. The first stage dealt with input variable definitions and capturing.

ii. Stage two of the computational process involved the processing of the input variables and their implementation in the main computational module of the demand estimation tool.

iii. The third stage was the development of the actual calculation engine, with the resulting traffic demands being generated for the underlying area.

iv. The final stage of the procedure is to allocate the resulting traffic demand from the sum of individual traffic in grids and map it into the traffic channels for subsequent resource allocation and cell configuration.

The model definition involves a methodological approach to the design and implementation of the software planning tool, *T-DET*. Each stage identifies functions that would be implemented as key modules of the tool. The sequence of the design methodology follows the following key steps:

Step 1: Geographic and demographic data input

In this stage, the identification of demographic information in terms of population densities and coverage areas are established from population and coverage maps. The population density of the area under study is finally used in estimating the number of potential mobile services subscribers in that area. From the signal coverage maps (best server areas) the size of the coverage area in km^2 is obtained. These input variables are used in the next module of data processing module of the traffic demand estimation.

Step 2: Data processing

Since information to be used in demand estimation is available from various sources and formats, the data processing stage involves pre-processing and conversion of some data formats to easily available formats. The maps obtained for Kigali area were in paper format and had to be digitised and geo-referenced. This data includes census data, land usage data, and traffic measurements.

Step 3: Traffic Estimation Stage

The estimation stage is the actual main module where the main calculation takes place. The implementation of this module is indicated in Appendix F.

The input variables to the traffic estimation procedures were the following:

- Size of the service area in km^2.
- Contour of the best server region around each base station site.
- Population on the service area.
- Service penetration rate.
- Traffic per user in milli-Erlang (mE).
- Weighting factors accounting for the geographical features of the service area as indicated in the Table 4.1. These figures indicate the relative weight associated with a certain land-usage feature and are only used for tuning operational site's capacity. The impact of weighting on adjusting the demand is a corrective measure that accounts for variations, for example, the traffic in a lake (water) is taken as 0 due to the fact that it is less likely to have many users in water, while the demand on a road is twice that of open space [18].

Feature	**Weight**
Road	2
Open space	1
Water	0
Road and building	3
Open space and road	3
Open space and water	1

Table 4.1: Weighting factors used in relationship to the geographical features

The previous section described the definition of key input parameters required in the estimation process. Traffic variations were introduced to ensure that the estimate will take into account the traffic demand for times where maximum traffic demand is expected. The estimate is then computed for the busiest hour of the busiest day in each of the three scenarios.

4.2 Traffic demand estimation process

Having established and captured the input variable defined in the previous sections, the intended coverage map is loaded into the tool and divided into twenty grids for detailed analysis. The design process is diagrammatically indicated in Figure 4.1 below. The boxes to the left of the diagram indicate to the left the source of input data, and the middle yellow boxes indicate the actual variables that are extracted. The computation follows stages A through D as indicated in the diagram.

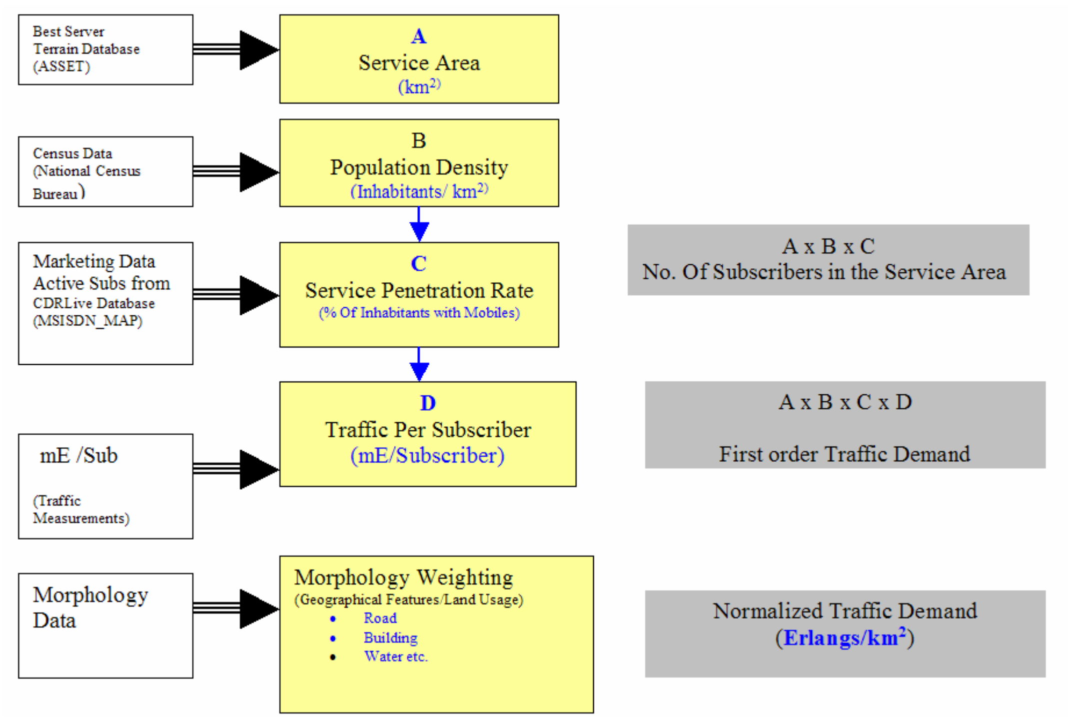

Figure 4.1: Computational procedures

4.2.1 The first order traffic estimation

Details of the traffic estimation procedure that were used in the terminal mobility model using user demographics were presented in the literature review. The following steps indicate estimation of the first order estimate.

i) The service area was dived into rectangular grids and its entire surface area noted.

ii) An initial average traffic demand per grid is computed by multiplying the traffic offered per user by the user population density in a service area.

iii) The user density is obtained by dividing the total population by the surface of the service area as noted in step i) above, and multiplying it by the service penetration rate

iv) The traffic demand estimated for the grids comprising the same best server region are summed up: this gives the traffic demand associated with each cell.

4.2.2 The second order traffic demand estimation

Normalization factors associated with each grid were computed based on underlying geographical features. The normalization factors are used to apportion the traffic offered in the service area to the best service regions and, ultimately, to the base station cells.

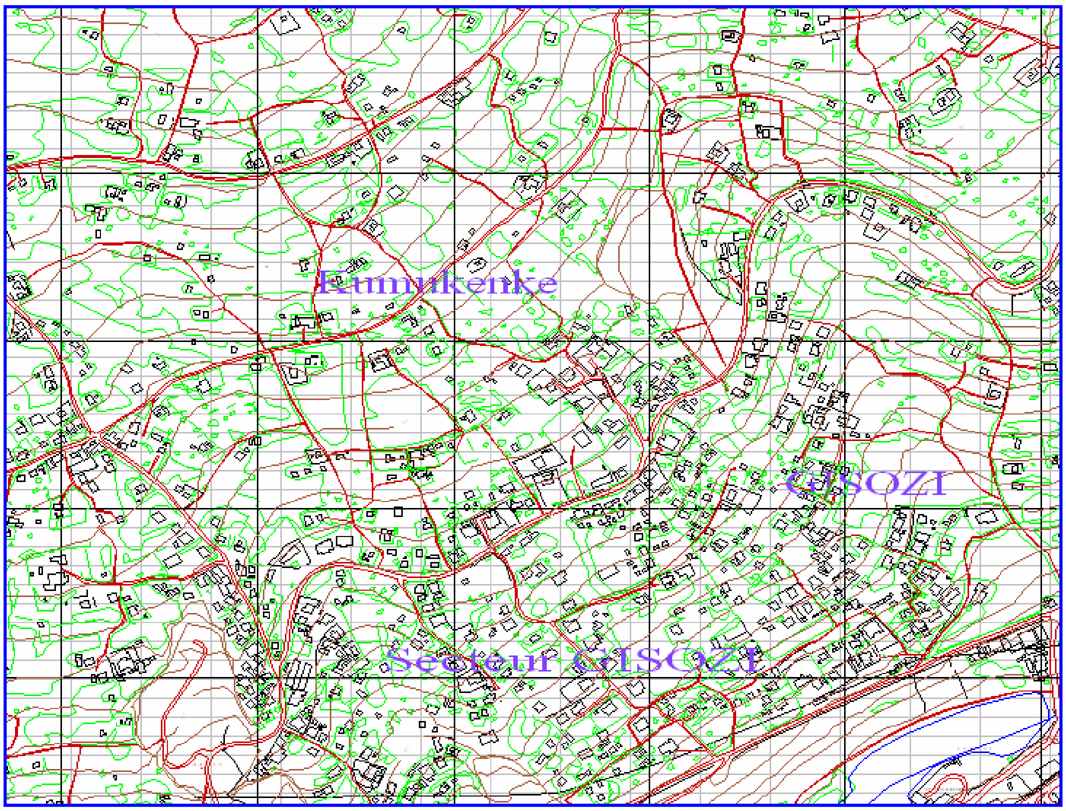

Figure 4.2: Grid of the area under study

4.3 The *T-DET* tool design and implementation

The tool takes input variables defined for the three scenarios presented in the previous sections and computes the resulting traffic demand for each of the three planning scenarios.

The user interface design was composed of an area classification and four data capture fields as indicated in the Figure 4.3.

The fields capture the Surface area of the best server, the population density of the area in which the service area belongs, the service penetration rate and the traffic per subscriber.

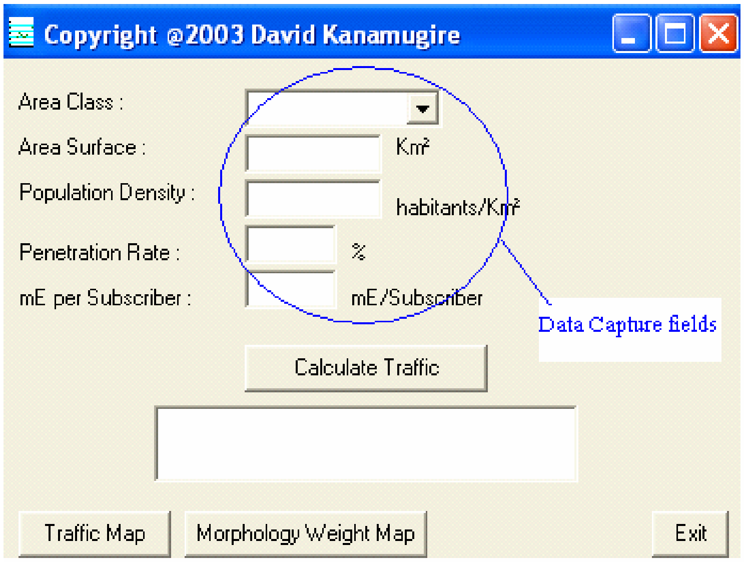

Figure 4.3: Input variable capture fields

The second part of the *T-DET* design is the traffic calculation. This part computes the first order traffic demand estimation based on the captured variables as described in the previous home or the home and at the lower section.

4.4 Generation of traffic demand matrix

The traffic matrix divides the loaded map into rectangular grids to allow for detailed study of a section of the entire service area on a higher resolution like a block of buildings. The number and arrangement of grids can be chosen based on the shape of the area, with edge grids being approximated to complete grids.

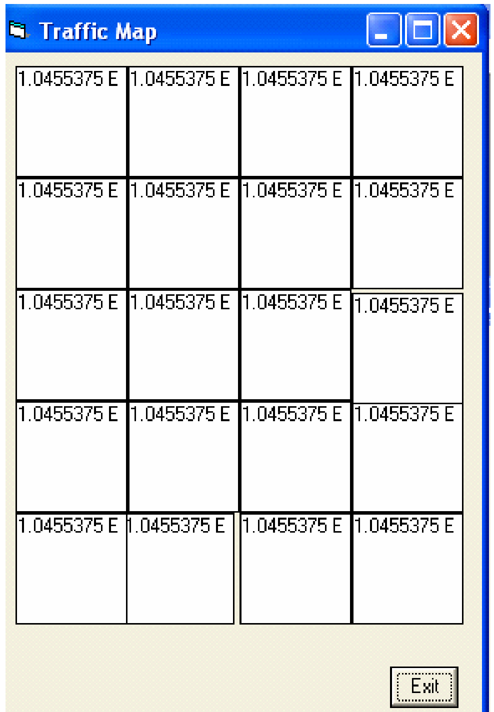

Figure 4.4: Traffic matrix generation

The calculated traffic is distributed in each grid. Grids that extend beyond the coverage area are weighted zero in the next normalization stage.

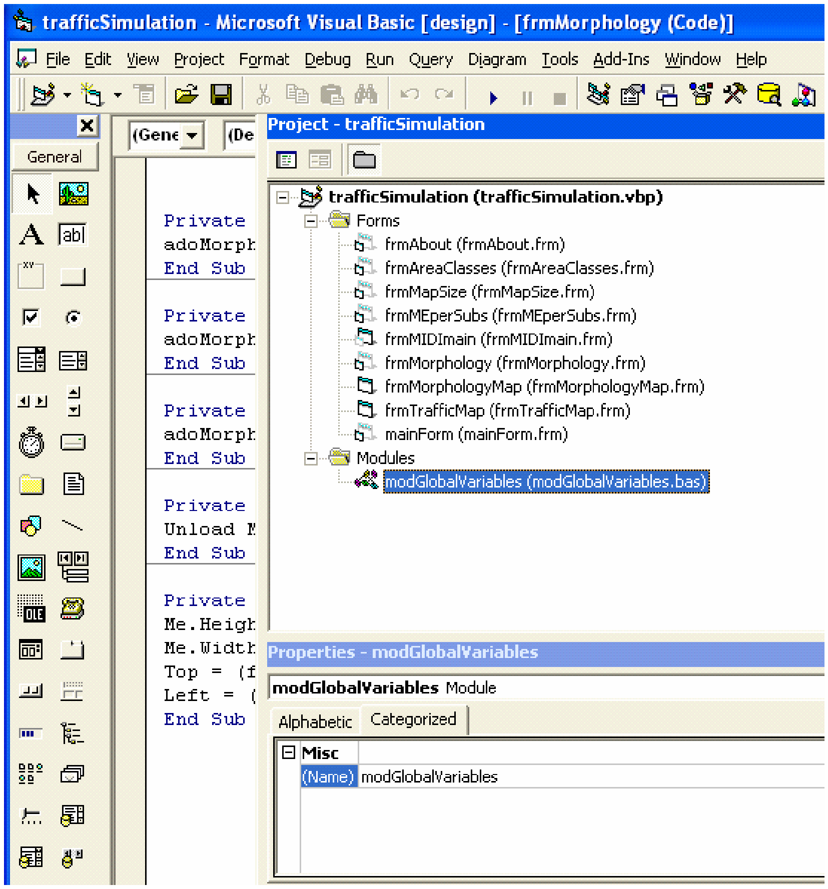

Figure 4.5: Main Program modules

4.5 The map loading feature

Once the first order traffic demand has been estimated, the area map was loaded into the tool by normal windows standard file opening procedure. Once loaded, the initial traffic map was then superimposed into the area map. Normalization involves adjusting of first order traffic estimates to improve the accuracy by use of traffic weighting factors associated with each grid on the area are computed based on underlying geographical features as indicated in Table 4.1.

The first order traffic demand per grid area calculated in the previous section is then multiplied by the weighting factor as indicated in the land usage weighting factors.

4.6 The tool calibration module

To further enhance the tool's capacity and improve its accuracy, the estimation parameters were designed to be calibrated when actual traffic measurements data is available or other demographic factors change. This is useful during operational stages of network operation where sufficient measurement data is available in traffic measurement database. The figure below indicates the parameters that can be defined in the database and later used for demand estimation.

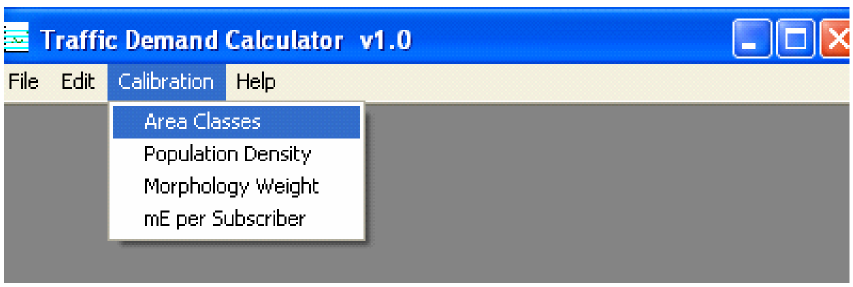

Figure 4.6: Calibration of Input Variables

4.6.1 Area class calibration

This feature allows operators to classify all the potential traffic sources into categories that exhibit their own classification criteria. This is to allow future integration with other planning tools that might be employing different classification procedures, or as more models evolve.

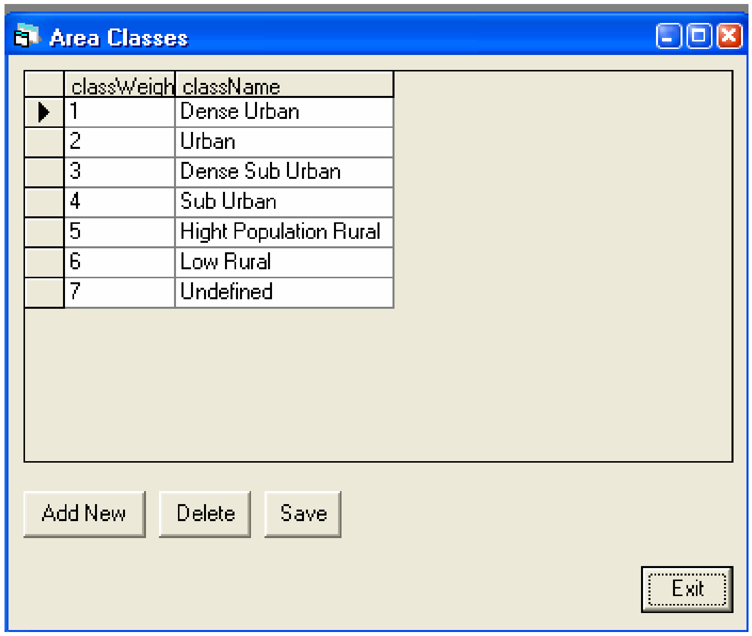

Figure 4.7: Definition of a New Area Class

4.6.2 Density calibration

Since census data varies or more accurate data is available from time to time, the tool allows the user to edit the population density as latest population data is available.

4.7.3 Morphology weighting indices

These settings can be modified to accommodate previously unknown land usage features and allocate different weights based on known traffic carrying potential in a similar environment.

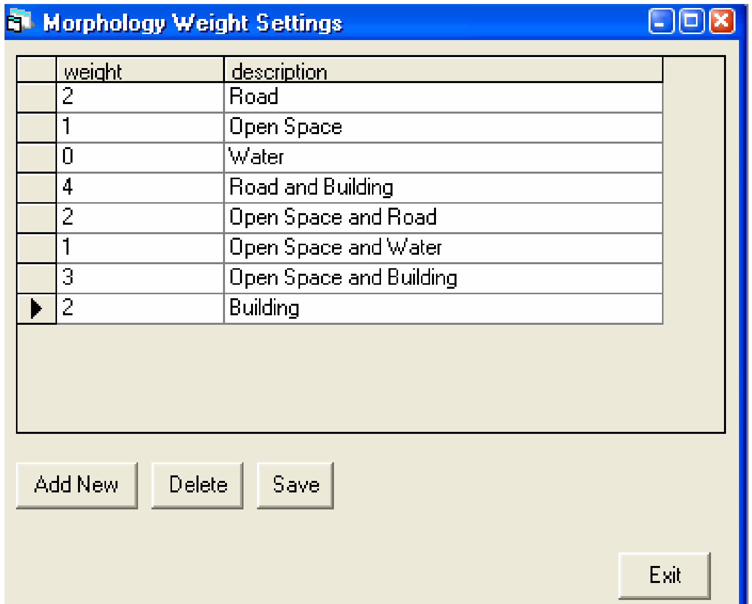

Figure 4.8: Calibration of weighing factors

4.7.4 Calibrating average traffic per subscriber

The traffic per subscriber indicates the average traffic in milli-Erlang that can be generated per subscriber. For network dimensioning purposes, a traffic intensity of 25 milli-Erlang is used for normal traffic conditions. This amount can be adjusted if actual measurements indicate a different intensity.

Figure 4.9: Calibrating average traffic per subscriber

4.8 Implementation of the T-DET computation algorithm

In this section, we combine all estimation procedures described in the previous sections to demonstrate the key computational stages implemented in *T-DET* tool. We use the *suburban residential* scenario to demonstrate both the *first* and *second orde*r traffic estimate iterations. Computation of traffic demand for other scenarios is similar and is presented in the next chapter in the presentation of results.

Having identified and characterised the site whose demand is to be estimated, a best server simulation is undertaken using propagation tool ASSET. The purpose of creating a best server is to ensure that sufficient signal coverage exists for users to camp on that site. The creation of the best server is indicated in Figure 3.2 and further explained in section 3.2. Once this has been obtained, the next step is to draw contours around the target cell to enable the calculation of the coverage area (area surrounded by a single contour) as indicated in Figure 3.4. This size of the area is computed automatically by ASSET and exported in an excel file for observation. In this scenario, the service area of the target cell was noted as 3.08 km^2.

The tools used and data type collected are indicated in Appendix I. In this section we detail how *T-DET* implements its computation based on previously defined input parameters. Actual computation, display of traffic values in the traffic matrix and map overlay procedures are performed by *T-DET* tool.

To perform the first order estimate in the suburban residential scenario, we consider the area characterised by:

- Suburban residential coverage area (A) = 3.08 km^2 as obtained from the coverage map in ASSET.

- Population density P_δ of 6116 inhabitants per km^2 as published by the census data [51].

The total population P, living in this area is then given by equation 4.1 below.

$$P = A^* P_\delta \tag{4.1}$$

P=3.08 *6116 = 18,837 Inhabitants

To get the number of potential subscribers, S, living in the area, we multiply the population size by the service penetration rate ρ. This value is established nationally by marketing statistics by estimating the number of users across a network as proportion of the entire population. This is an economic function, and is continuously calculated by the mobile operators as subscriber numbers change. It does not take into consideration other factors like churn. For Suburban residential areas the figure is established as 25 subscribers per every 1000 people. The number of potential subscribers residing in the area is given by equation (4.2).

$$S=P^* \rho \tag{4.2}$$

=18,837 *0.025=471 subscribers

Given that the area has a potential subscriber base of 471 subscribers, we proceed to estimate traffic demand to serve this area. Using the assumption that average user generates 25 mE during busy hour [18].We calculate traffic demand, T as:

$$T=S^*0.025 \tag{4.3}$$

T= 471*0.025= **11.75** Erlang

This estimate is based on the assumption that traffic demand is evenly distributed across the entire service area. This is rarely the case, and this assumption leads to discrepancies between the *first order* estimate and the *actual traffic* measurements. To address this discrepancy, relative weighting indices (normalisation factors) are used to account for uneven distribution within the area caused by different underlying features in the area. Such weights are given in Table 4.1. These weights are established based on the fact that different featured contribute differently to communications traffic potential.

The traffic demand in build-up areas for example, is higher than that in open areas, while areas covered by water (despite by the size of the area) have negligible impact on traffic demand in a specific area.

In the *second order* estimation (normalisation stage), the traffic matrix map is generated by the tool and superimposed onto the area map. The underlying features contributing to different traffic conditions are then noted. The tool then computes new traffic demand, taking into consideration these new weights. Since these raster maps are used, the areas are noted visually by observing these features on the maps.

To apply the weighting indices presented in table 4.1 to the area, we use the following guidelines:

- Areas within the matrix map that fall outside the coverage area are given weights of zero.
- Grid areas that exhibit high concentration of buildings are weighed 3 and those areas that are sparsely populated but with roads are given weights of 1.
- Grid areas that are partially occupied by buildings are assigned a weight of 2.
- Areas that fall outside the coverage area are weighted 0

Figure 4.10 indicates the weight distribution matrix superimposed onto the area map.

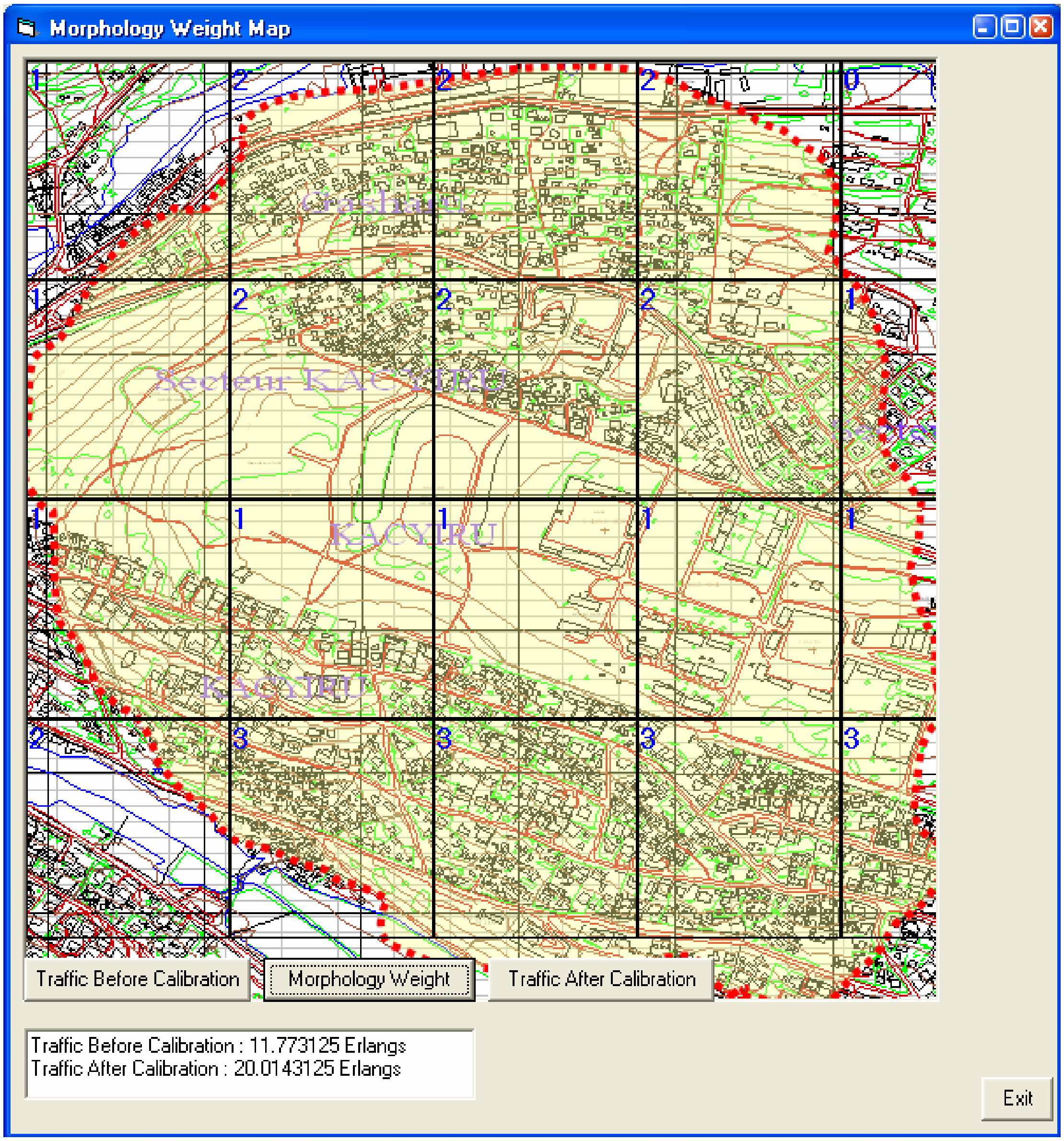

Figure 4.10: Weight distribution across traffic matrix

The resulting traffic demand per grid is calculated by multiplying the underlying weight by the traffic demand established in the first order estimation stage. This results in the new traffic map as indicated in Figure 4.11. The second order traffic estimate is then obtained by summing up all the new traffic in all the grids.

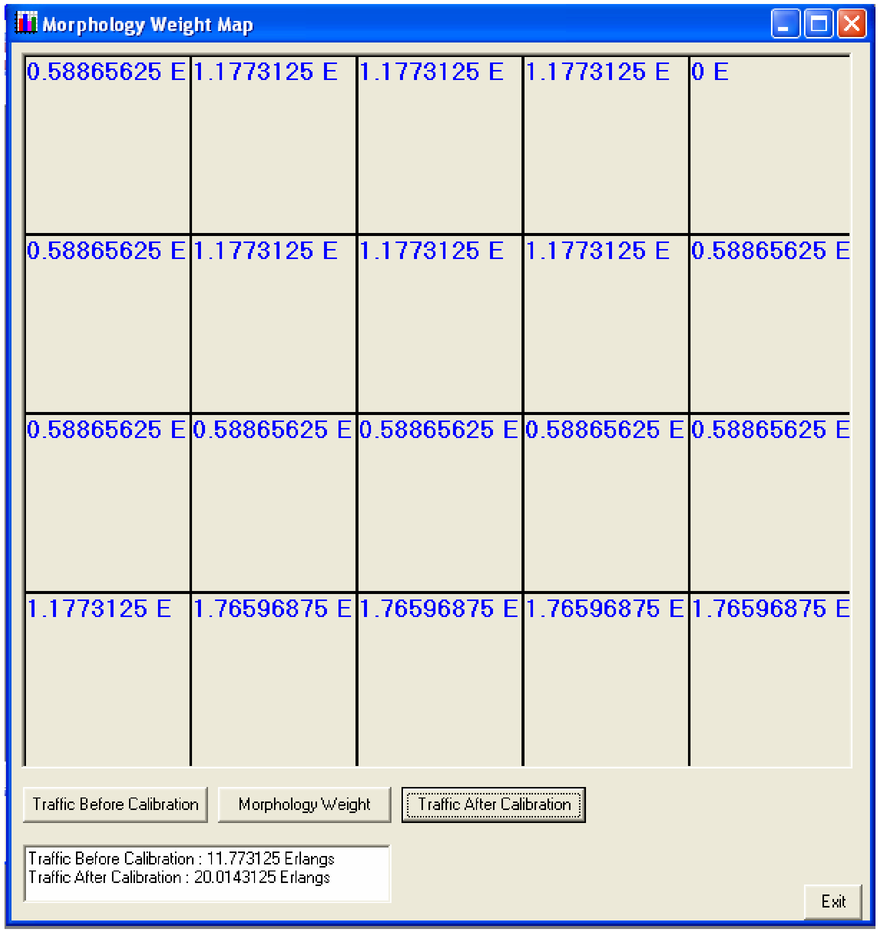

Figure 4.11: Normalised traffic matrix

The second order total traffic demand is obtained by summing up all the traffic demand in individual grids indicated in Figure 4.11. The sum of all the individual grid traffic in the above figure is then given as 20.01 Erlang and it is this value that is use in capacity dimensioning and subsequent resource allocation.

4.9 Conclusion

This chapter presented the methodology used in calculation of the traffic demand for the three planning scenarios in the Kigali suburban commercial, suburban residential and rural areas. The computational algorithm used by the estimation tool was demonstrated by one of the scenarios.

Having obtained the input variables that characterise the area under study into the three classes, *suburban commercial*, s*uburban residential* and *rural* areas, the first iteration computed the traffic demand in each of these areas based on demographic factors. To improve the accuracy of the tool, a provision was made to calibrate the value of the input variables resulting in a tuneable tool that could be used in a real planning environment. Presentation and analysis of the computational results is presented in the next chapter.

CHAPTER 5

PRESENTATION OF 'T-DET' RESULTS

5.1 Introduction

In this chapter the results obtained by the traffic demand estimation tool, *T-DET*, in the three planning scenarios are presented. The iterations include the first order traffic estimates are based on characterisation of the area as described in chapter 3 of this study. In cases where these estimates are unrealistic, further improvement of the results is possible by accounting for other factors in the tuning process.

5.2 Suburban commercial area

The following sections present the results for the suburban commercial area. Three iterations were conducted. To validate the accuracy of the estimates, these estimates are compared with actual traffic measurements.

5.2.1 First order estimates

The table below describes the characterization of the suburban commercial area, in terms of required input variables for the computation of first order estimates.

Input Variable	Value
Service Area (km^2)	2.88
Population density (Inhabitants/ km^2)	12616
Population Size (No. of Inhabitants)	36334
Service Penetration Rate (Subscribers/1000 inhabitants)	0.025
Number of Subscribers	908
Traffic per Subscriber (milli-Erlang)	25

Table 5.1: Characterisation of Suburban commercial area

The first order traffic estimate results for this area are presented in Figure 5.1 below.

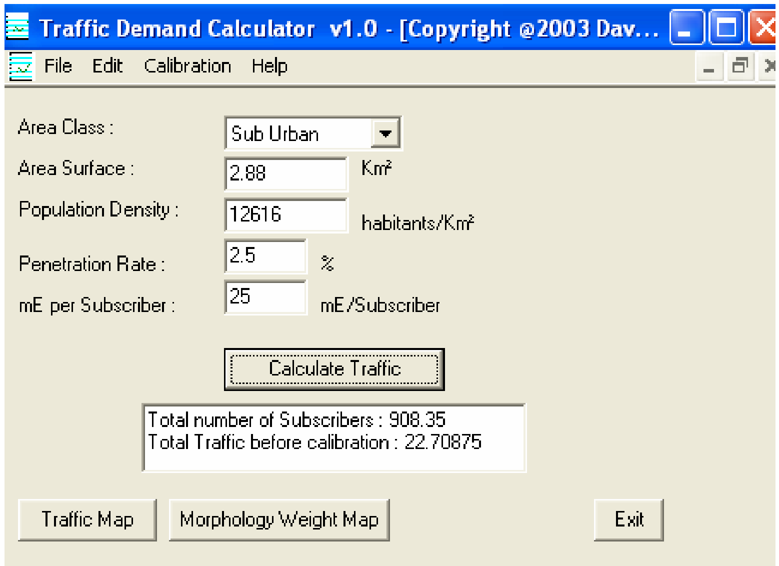

Figure 5.1: First order Suburban Commercial traffic estimation

5.2.2 Second order estimates

The first order estimates indicate the need to fine tune the model to accommodate for the measured peak traffic of 28 Erlang, which would require 5 transceivers. In this particular scenario however, we are limited to installing only 4 physical transceivers units (TRU) in an individual cabinet that we can accommodate in a single base cell. Installing 5 transceivers in a single cell cabinet would result in heavy signalling load, resulting in high *call setup failure rate* (%SFAIL) due to signalling channel congestion (SDCCH). Rather than use weights to accommodate for this change, we utilise other optimisation means like cell load sharing between neighbouring cells to accommodate the extra traffic load.

5.2.3 Actual traffic measurements

The figure below indicates actual 30 day busy hour traffic measurements for suburban commercial measurements, depicting a high peak of 28 Erlang.

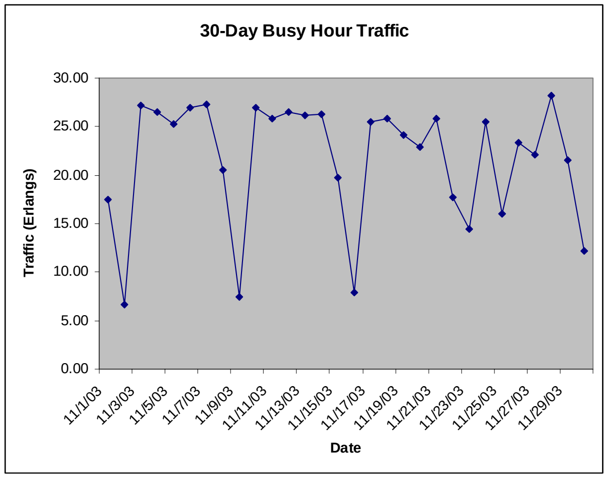

Figure 5.2: Suburban Commercial Traffic Measurements

5.3 Suburban residential area

The suburban residential area, situated in the outskirts of the capital Kigali was characterised by the input variables indicated in Table 5.2 below.

5.3.1 First order estimates

The input variables that characterize the KICUKIRO area, a suburban residential area about 6 km outside Kigali city centre are given in the table below.

Input Variable	Value
Service Area (sq. km)	3.08
Population density (Inhabitants/km2)	6116
Population Size	18837
Penetration Rate (No. of Subs/Total Population)	0.025
No. of Subscribers	471
Traffic per Subscriber (mE)	25

Table 5.2: Characterisation of Suburban commercial area

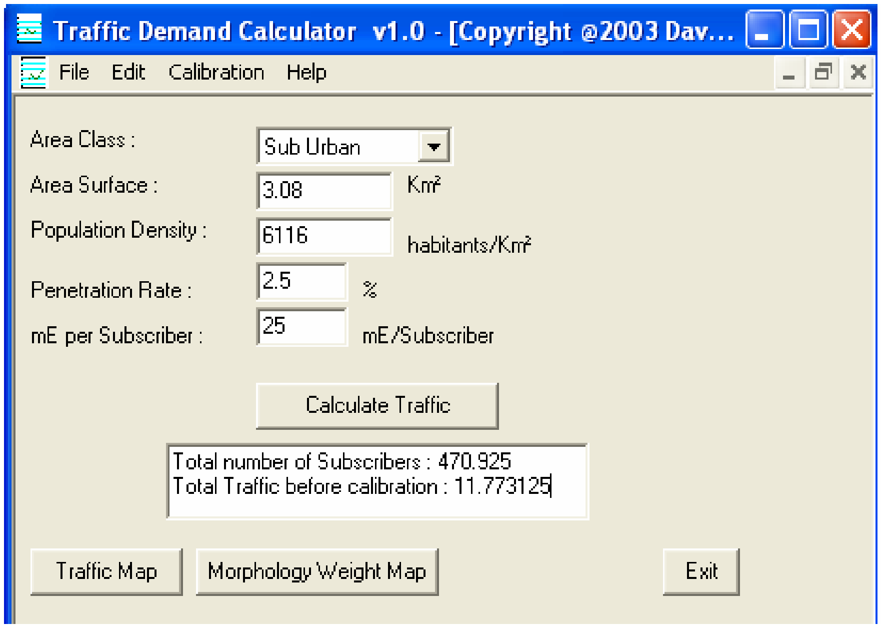

Figure 5.3 First order Suburban residential traffic estimation

5.3.2 Second order estimates

The second order estimation process for the suburban residential scenario is indicated in the area map in appendix G. The areas are weighted and the resulting traffic demand becomes 20.0143 Erlang. The procedure for second order estimation has been detailed in section 4.8.

5.3.3 Actual traffic measurements

The third iteration is the capturing of the actual traffic measurements in the traffic measurements database. Appendix C indicates how these results are obtained using Structured Query Language (SQL) queries. The first order estimates 11.77 Erlang traffic demand and on normalisation produces 20 Erlang.

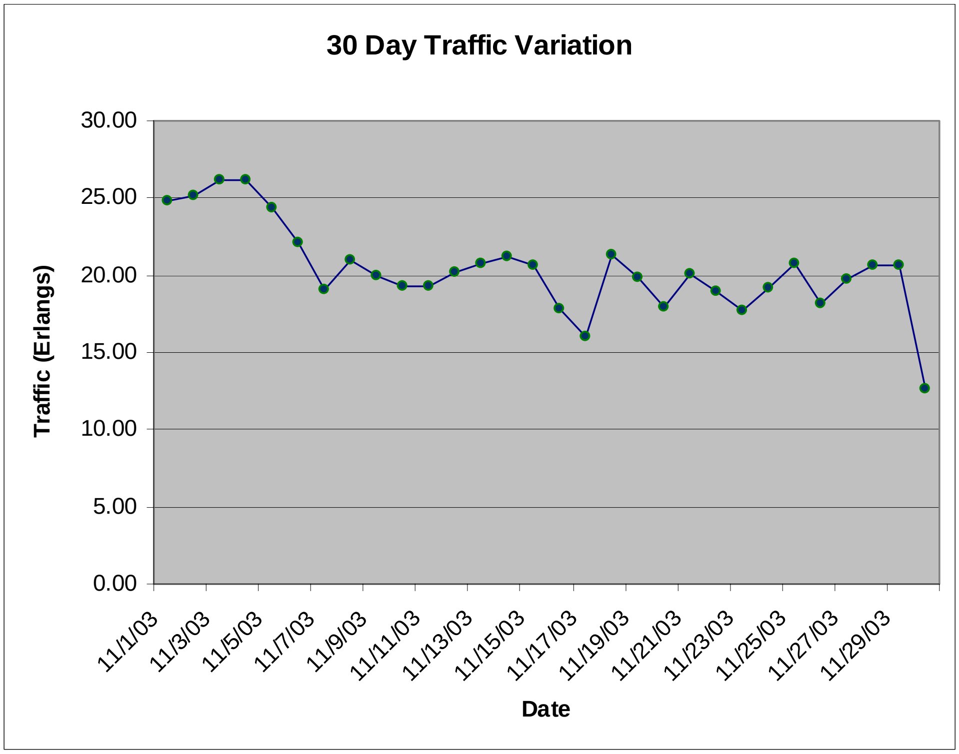

Figure 5.4: Suburban Residential Traffic Measurements

The graph above indicates the 30-day busy hour traffic measurements. The average traffic demand is 8.13 Erlang.

5.4 Rural area

Table 5.3 below indicates the input variables that characterise the rural area.

Input Variable	***Value***
Service Area (km^2)	23.67
Population density (Inhabitants/ km^2)	6289
Population Size	148860.63
Penetration Rate (No. of Subs/Total Population)	0.0025
No. of Subscribers	372
Traffic per Sub.	0.025

Table 5.3: Rural area characterisation

5.4.1 First order estimates

The results of the first order estimates for the rural area as computed by the estimation tool are indicated in figure 5.5 below. The computed traffic demand is 9.3 Erlang.

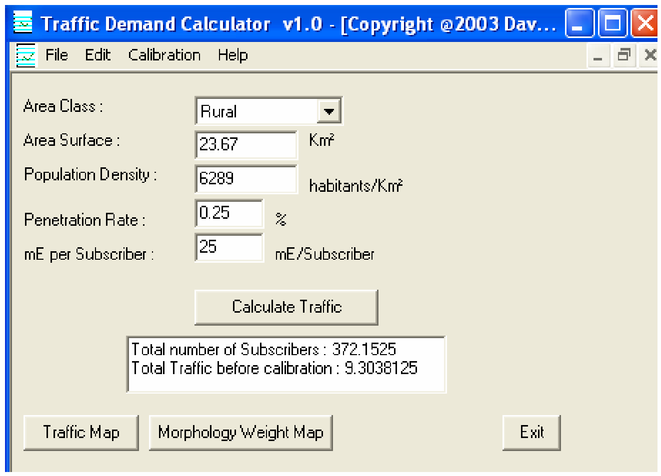

Figure 5.5: First order rural area traffic estimation

5.4.2 Second order estimates

Appendix G indicates the weighting factors and the resulting traffic demand of 6.9778, approximated to 7.0 Erlang.

5.4.3 Actual traffic measurements

Figure 5.6 below indicates traffic measurements in the rural area. Note that the traffic variation in rural area is not as much as in other scenarios. The reason for this could be attributed to limited mobility in these areas.

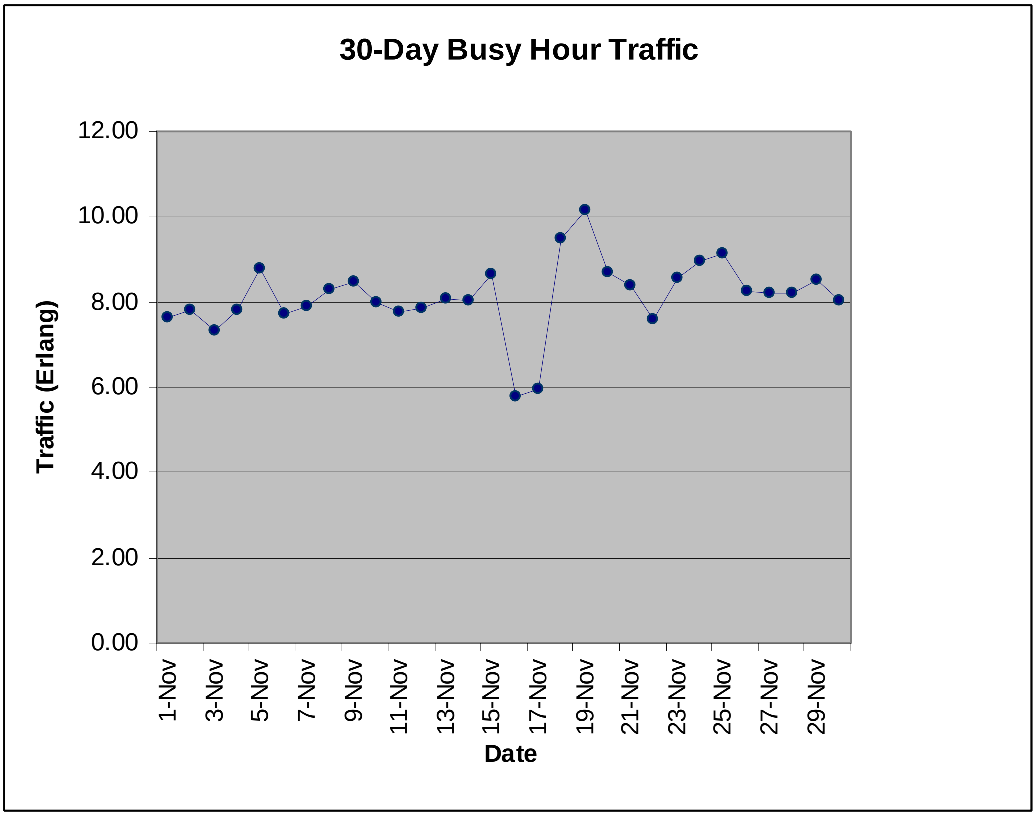

Figure 5.6: Rural area traffic measurements

5.5 Conclusion

This chapter presented traffic demand estimation results in the three planning areas under study. A detailed analysis and application of these results in optimum design and configuration of a cell in the network is presented in the next chapter.

C H A P T E R 6

APPLICATION OF 'T-DET' RESULTS IN NETWORK DESIGN

6.1 Introduction

In this chapter, we present and analyse the traffic demand estimation results obtained in *Chapter 5.* As was the purpose of this study, these results are then applied in obtaining the desired optimum capacity configuration that would result in better resource utilisation and quality improvement by minimisation of system congestion. Further application of these results in traffic demand forecasting; given population growth information is also indicated.

6.2 Determination of capacity configuration based on obtained results

After having established the traffic demand in a given area, the next step in the process is to determine the number of the required radio channels and the corresponding transceivers to carry the estimated traffic demand. The cell capacity configuration, which is the number of required transceivers N_{TRX} within the base station, is obtained from Table 6.1 below by the use of Erlang-B formula.

# TRX	1	2	3	4
# physical. time-slots	8	16	24	32
# control. channels	1	2	2	3
# FR traffic channels	7	14	22	29
Traffic cap. (2% block.)	2.9 Erl	8.2 Erl	14.9 Erl	21.0 Erl

Table 6.1: Erlang-to-Traffic Channels Mapping

6.3 Determination of resource utilisation levels

Table 6.2 indicates the number of full rate traffic channels required for the three scenarios and the resulting percentage utilisation. Given that full traffic at a 2% blocking probability results in 100% resource utilisation, the percentage utilisation U is then calculated as:

$$U = 100 \frac{A_{estimate}}{A_{cap(2\%Block)}} \tag{6.1}$$

Where $A_{estimate}$ the calculated traffic is estimate and $A_{cap(2\%Block)}$ is the full traffic capacity at 2% blocking probability. The calculated percentage utilisation levels using Equation 6.1 are indicated in table 6.2 below.

Area Category	Estimated Traffic demand ($A_{estimate}$) Erlang	Required Capacity (2% GoS) ($A_{cap(2\%Block)}$)	Full Rate TCH	Cell Configuration (N_{TRX})	Resource Utilisation (%)
Suburban Commercial	22.70	21	29	4	108.00
Suburban Residential	20.01	21	29	4	95.57
Rural	7.00	8.2	14	2	85.37

Table 6.2: Resource allocation based on previous results.

6.4 Forecasting traffic demand based on current results

With the tool results providing base traffic load in a given service area of a network, it is possible to undertake traffic forecast. It is important to understand however, that the following assumptions were considered during this study:

First assumption is that the population growth in Rwanda is maintained at the current 0.26 % for the next 5 years (no drastic change in mortality rate, fertility rate and migration)

Second, the service penetration rate of 77% as estimated by the ITU-Telecommunications Indicators for Africa is attained.

The average revenue per user [ARPU], according to the UN estimates [54], is currently estimated to be 18 US$. It is however expected to fall as the market becomes more deregulated and competition grows.

To estimate the expected revenue generated in each of these planning areas in year 2010, we assume the future population in each of these areas and multiply this by the monthly average revenue per user (ARPU) .In the table below, the expected revenue is calculated by multiplying the projected subscriber base with the ARPU.

Area Class	Base population (2005)	Projected Subscriber base (2010)	5-Year traffic demand forecast (Erlang)	Expected Monthly revenue (US$)
Suburban commercial	1262	2234	55.84	40212
Suburban Residential	471	834	20.84	15012
Rural	372	658	16.46	11844

Table 6.3: Five year demand and revenue projection

6.5 Cost benefits of optimum capacity design

i. From the utilisation figures indicated in table 6.3, it can be seen that system is optimally utilised as near to 100% as possible.

ii. There is better resource savings in low traffic areas (rural) resulting in cost savings. It was found that for the estimated traffic one transceiver would be installed instead of two, resulting in a saving of transceiver valued at 15 000US$.Network wide savings would be realised in optimum equipment installations.

iii. With accurate estimates, there could be better traffic balancing across a network leading to overall better utilisation and congestion minimisation

iv. Figure 6.1 below indicates reduction in percentage congestion, PCONG (in Red) for a suburban commercial area from an average of 8% during busy hour to 0.7.

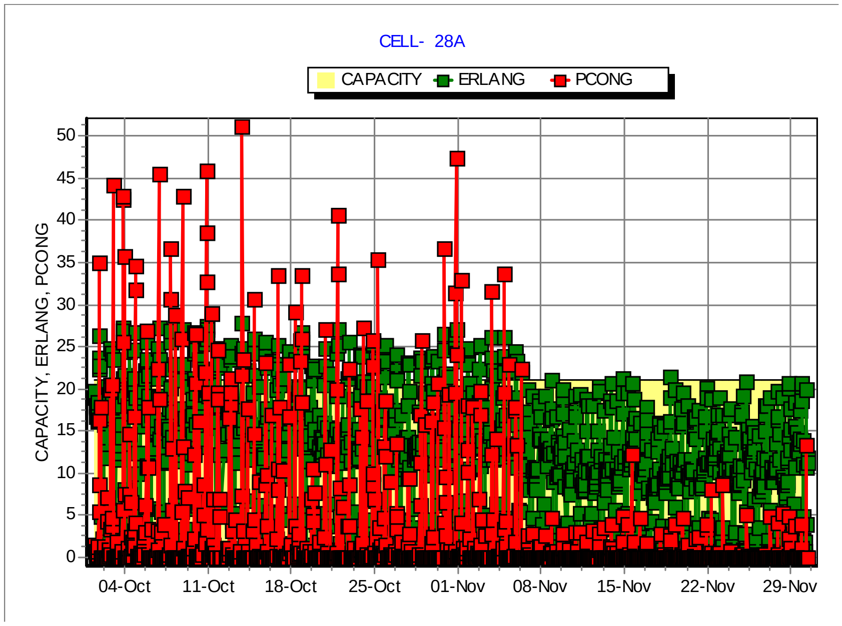

Figure 6.1: Indication of Congestion reduction

Figure 6.1 above indicates the impact of optimisation based on accurate estimation of traffic demand. The graph, captured from live network statistics using OPTIMA planning tool by Aircom, indicates a significant drop in congestion from average of 8% to 0.7% on 08-Nov, on Cell 28A. This reduction in system congestion can be translated into actual short and long term cost savings. The table below indicates comparison of loss of revenue before system optimisation (at 8% congestion) and after optimisation (0.7%).

	PCONG=8%	PCONG=0.7%
Percentage Congestion	8%	0.70%
Call attempts	4000	4000
Blocked calls	320	28
Lost Revenue (day) at 0.3 US$ per min	$96	$8
Lost Revenue (Month)	$2,880	$252
For a network of 300 Cells (Per Month)	$86,400	$7,560
Estimated Revenue Loss (5 Years)	$5,184,000	$453,600
Revenue Savings	$4,730,400	

Table 6.4: Cost benefit due to congestion reduction

6.6 Analysis of obtained results

Table 6.5 below shows the results of the three iterations for the planning scenarios under study. After the results are obtained, the planning engineer uses these results for allocating necessary resources in terms of transceivers to handle the prevailing traffic. Knowledge of the prevailing traffic in a given area is a critical input to future planning and optimisation of the GSM cellular network.

Area Class	1st Order Estimate	2nd Order Estimate	Measurement
Suburban Commercial area	22.7	22.7	21.66
Suburban Residential area	11.77	20.01	20.32
Rural area	9.39	7	8.13

Table 6.5: Comparison of final results

The table indicates comparison between the first order traffic estimates, the second order estimates and the actual busy hour traffic measurements taken for one month. The second order estimates are very close to the actual measurements indicating high accuracy of the method. A great improvement is noticed in suburban residential area with the use of weighting factors.

Further methods for improving the tool accuracy in rural areas are suggested for further research in chapter 5.

6.7 Conclusion

This chapter presented and discussed key results of the study conducted in three planning scenarios namely, suburban commercial, suburban residential and rural areas.

Practical implications of these results on the accuracy of the estimation procedure are presented and improvement of first order traffic estimation by using weighting method based on ITU-T recommendation E.760 dealing with terminal mobility traffic model in mobile networks has been indicated.

With knowledge of demographics, the tool can be used to predict the future traffic demand in a given service area.

The computation module will take input variables and estimate traffic demand given the coverage area in $km^{2,}$ the population density (inhabitants / km^2) and the service penetration rate. For benchmarking purposes, the initial traffic potential that can be generated by each subscriber is assumed to be 25 mE. These initial estimates can then be used to allocate the necessary resources that can be tuned later when either the input variables change or actual measurements used, to further improve the accuracy.

C H A P T E R   7

CONCLUSIONS AND RECOMMENDATIONS FOR FURTHER RESEARCH

7.1 Review of purpose and objectives

The purpose of this study was to design and develop a simple yet accurate network design tool, T-DET, which uses locally available data to estimate available traffic demand in a given service area of cellular network in Rwanda. From the results of the tool, the following objectives were achieved:

i. Maximising resource utilisation by allocating optimum capacity resources.
ii. Improved Quality of Service by reducing system congestion.
iii. Gain pre-operational knowledge about expected traffic and hence expected revenue.

The study first reviewed existing methods of traffic demand estimation and their limitations in practical operation of cellular networks in general. Specific limitations in African operational environment where there is severe shortage of telecommunications engineering expertise and lack software design tools were then considered. The study was conducted in three planning environments Suburban Commercial, Suburban Residential and Rural scenarios. These classifications are typical of many African operational environments that do not have large metropolitan cities.

7.2 Review of the traffic estimation process

The traffic demand estimation process for the three planning scenarios under study was conducted in a phased approach. This involved first generating a coverage map for the area under consideration and establishing the coverage area. The population density map was then superimposed onto the coverage map to establish the number of subscribers per grid within the area. By multiplying the number of subscribers per grid, with the mean traffic generation subscriber, traffic demand for that area was obtained.

Where first order traffic demand estimates were inaccurate, weighting factors that are based on land-usage factors like buildings and roads, that affect traffic distribution differently were utilised, resulting in more accurate estimates. Traffic channels and consequently transceivers and base station configuration are designed based on the Second Order traffic demand.

7.3 Conclusions and summary of important findings

In this study, the following were achieved:

1. A *Demand Based Methodology* was evaluated.
2. A tool (T-DET) was built that can conduct accurate Traffic Demand Estimation. The output can be used together with other Planning tools (MapInfo, ASSET, etc.) To enable network planning engineers in capacity design, network dimensioning and demand forecasting
3. A method to Forecast Traffic Demand and Expected Revenue was validated.

The T-DET results indicated three important findings:

a) With accurate traffic estimation, high utilisation figures were realised resulting in cost savings

b) There was improved quality by reduction of system congestion

c) Five year traffic forecasting was realised, rendering the tool usable in Greenfield conditions where no actual measurements are available.

From better resources utilisation, cost saving due to reduction in the number of actual deployed transceivers (TRX) can be established. Assuming an over capacity of 30 radio transceivers in the suburban commercial rural scenarios, and 20 transceivers in the suburban residential area, the cost savings would amount to US $ 300 000 and US $750 000 respectively at a cost of 15 000 US$ per transceiver unit (TRX). The results of the study also indicated that a very high system utilisation figure of 104.76 % was achieved in suburban commercial areas. Suburban residential and rural area exhibited 95.24 and 85.37 percentage utilisation respectively as indicated in Table 6.2.

The system congestion reduced from an average of 8% during busy hour to 0.7% in suburban commercial area as indicated in Figure 6.1. A drop in percentage congestion (PCONG) minimised call setup failure and improves the regulated grade of service which is set at 2% for Rwanda. Using the base penetration rate obtained in three planning scenarios, 5 year traffic demand forecasts and expected revenue was determined. The forecasts indicate that mobile service penetration will grow to 77% in the country and the average revenue per user (ARPU) will drop from 18 US $ to 10 US $.

7.4 Recommendations for further research

The accuracy of the tool and its ability to predict future traffic demand would be greatly facilitated by the availability of vector based demographic data, which could easily be imported in T-DET computation module. This would allow association of key metrics to one unique grid producing a direct relationship between land usage, demographic characteristics and prevailing traffic demand, thereby allowing auto-update when any of the metrics changes. The impact of other socio-economic factors like increase in subscriber income levels, impact of communications costs and tariffs that impact the average traffic demand and subsequently capacity demand and network configuration needs further investigation.

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APPENDICES

APPENDIX A: DEFINITION OF TERMS USED

Connection

An association of resources providing means for communication between two or more devices in, or attached to, a telecommunication network.

Resource

Any set of physically or conceptually identifiable entities within a telecommunications network, the use of which can be unambiguously determined.

User

Any entity external to the network which utilizes connections through the network for communication.

Telecommunications traffic; teletraffic

A process of events related to demands for the utilization of resources in a telecommunication network.

Poisson traffic; pure chance traffic

Traffic that has a Poisson distribution of arrivals

Traffic intensity

The instantaneous traffic in a pool of resources is the number of busy resources at a given instant of time. In applications, the term traffic intensity usually has this meaning of mean traffic intensity.

Traffic intensity is equivalent to the product of arrival rate and mean holding time. The unit of traffic intensity is the Erlang (symbol: E).

Erlang

Unit of traffic intensity (symbol: E). 1 Erlang is the traffic intensity in a pool of resources when just one of the resources is busy.

Traffic volume

The traffic volume in a given time interval is the time integral of the traffic intensity over this time interval. It is equivalent to the sum of the holding times in the given time interval.

Its unit is Erlang hour (symbol: Eh). The traffic volume in a given time interval is the time integral of the traffic intensity over this time interval

Idle (state)

Condition of a resource that is free to be seized.

Busy (state)

Condition of a resource following its seizure.

Holding time

The time between the seizure of a resource and its release.

Blocked mode of operation

A mode of operation in which bids, which find no suitable resources idle and accessible, are not permitted to wait.

Delay mode of operation

A mode of operation in which bids which find no suitable resources idle and accessible are permitted to wait.

Call congestion

The probability that a bid to a particular pool of resources will not result in an immediate seizure.

Time congestion

The proportion of time that a particular pool of resources does not contain any idle resource.

Waiting time; queuing time

In delay mode of operation, the time interval between the bid for a resource and its seizure.

Call attempt

An attempt to achieve a connection to one or more devices attached to a telecommunications network.

Blocked call attempt

A call attempt that is rejected owing to a lack of resources in the network.

Completion ratio

The ratio of the number of completed call attempts to the total number of call attempts, at a given point of a network.

Answer seizure ratio (ASR)

On a route or a destination code basis, and during a specified time interval, the ratio of the number of seizures that result in an answer signal, to the total number of seizures.

Answer bid ratio (ABR)

Ratio of bids that result in an answered signal to the total number of bids.

Grade of service (GoS)

A number of traffic engineering variables used to provide a measure of adequacy of a group of resources under specified conditions. These grades of service variables may be probability of loss, dial tone delay, etc.

Quality of service (QoS) variable

Any performance variable (such as congestion, delay, etc.), which is perceivable by a user.

Blocking

The probability that any call attempt will be unsuccessful due to a lack of network resources.

Busy hour

The continuous 1-hour period, lying wholly in the time interval concerned for which the traffic or the number of call attempts is greatest.

Average daily peak hour traffic

The average busy hour traffic of several days. It is usually not related to the same hour each day.

Time consistent busy hour

The 1-hour period, starting at the same time each day for which the average traffic of the resource group concerned is greatest over the days under consideration.

Traffic carried

The traffic served by a pool of resources.

Traffic offered

The Traffic that would be carried assuming availability of an infinitely large pool of resources.

Effective traffic

The traffic corresponding only to the conversational portion of effective call attempts.

Lost traffic; abandoned traffic

That part of the blocked traffic that does not result in reattempts.

Suppressed traffic

The traffic that is withheld by users who anticipate a poor quality of service (QOS) performance.

Origin (of a call)

The location of the calling network termination. This may be specified to whatever accuracy is necessary.

Traffic matrix

A structured presentation of the traffic between a number of origins and destinations.

Originating traffic

Traffic generated within the network considered, whatever its destination.

Terminating traffic

Traffic which has its destination within the network considered, whatever its origin.

Traffic distribution imbalance

Unevenly distributed traffic among similar resources.

Handover

In mobile cellular systems, a system-driven change of the current association between an established connection and a channel (mobile to base station and/or base station to mobile channel) in the radio segment spanned by one cell.

APPENDIX B: PERFORMANCE QUERIES

```
select
TRUNC(SDATE) Sdate, cell, round(avg(dtch), 0) DTCH, sum(TMSESTB) SuccCalls,
ROUND((NVL(SUM(ERLANG), 0)*60)/((0.05+(NVL(SUM(TNDROP)+1E-20,
    0)+NVL(SUM(TSNDROP), 0)+NVL(SUM(THNDROP), 0)))), 2) AS "MINUTE
    PER DROP",
ROUND(100*(NVL(SUM(TASSALL), 0)-NVL(SUM(TCASSAL), 0)-
    NVL(SUM(THCASAL), 0)-NVL(SUM(TSCASAL), 0)+NVL(SUM(TNDROP),
    0)+NVL(SUM(THNDROP), 0)+NVL(SUM(TSNDROP),
    0))/(NVL(SUM(TASSALL)+1E-20, 0)+0.01), 2) AS "%CALL FAILURES",
ROUND(100*(NVL(SUM(CCALLS), 0)-NVL(SUM(CMSESTB),
    0)+NVL(SUM(CNDROP), 0))/(NVL(SUM(CCALLS)+1E-20, 0)+0.01), 2) AS
    "%CONTROL FAILURES",
ROUND((NVL(SUM(TNDROP), 0)+NVL(SUM(TSNDROP),
    0)+NVL(SUM(THNDROP), 0))/(NVL(SUM(TCASSAL)+1E-20,
    0)+NVL(SUM(THCASAL), 0)+NVL(SUM(TSCASAL), 0))*100, 2) AS "%DROP
    CALLS",

ROUND((NVL(SUM(TCONGS),0)+NVL(SUM(TSCONGS),
    0)+NVL(SUM(THCONGS), 0))/(NVL(SUM(TMSESTB)+1E-20,
    0)+NVL(SUM(THSESTB), 0)+NVL(SUM(TSMSEST), 0)+NVL(SUM(TCONGS),
    0)+NVL(SUM(TSCONGS), 0)+NVL(SUM(THCONGS), 0)+0.01)*100, 2) AS
    "%CONGESTION",
```

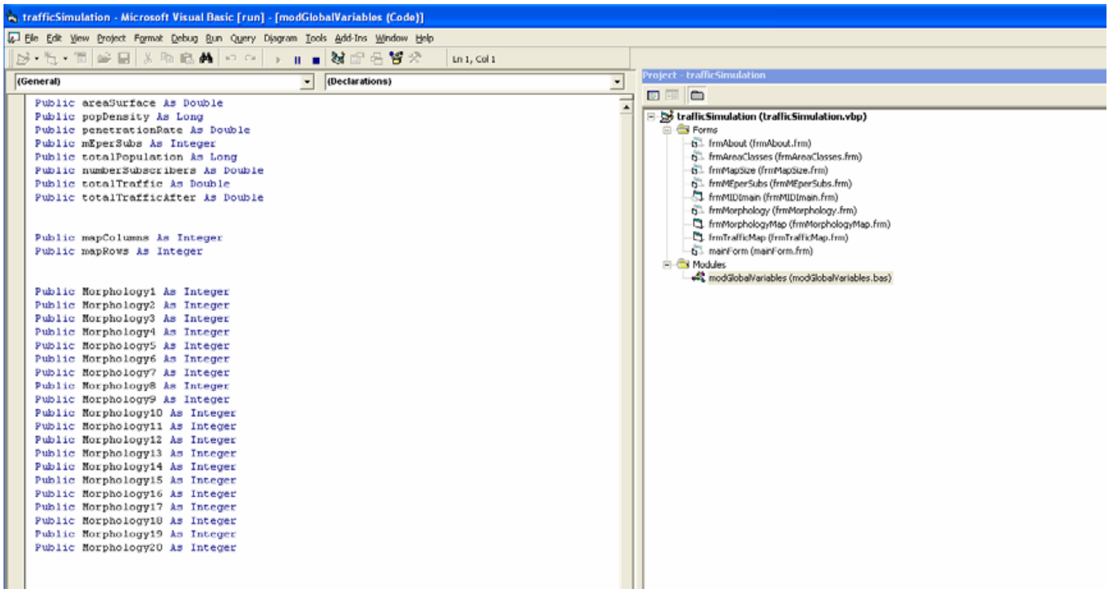
APPENDIX C: TRAFFIC MEASUREMENTS QUERIES

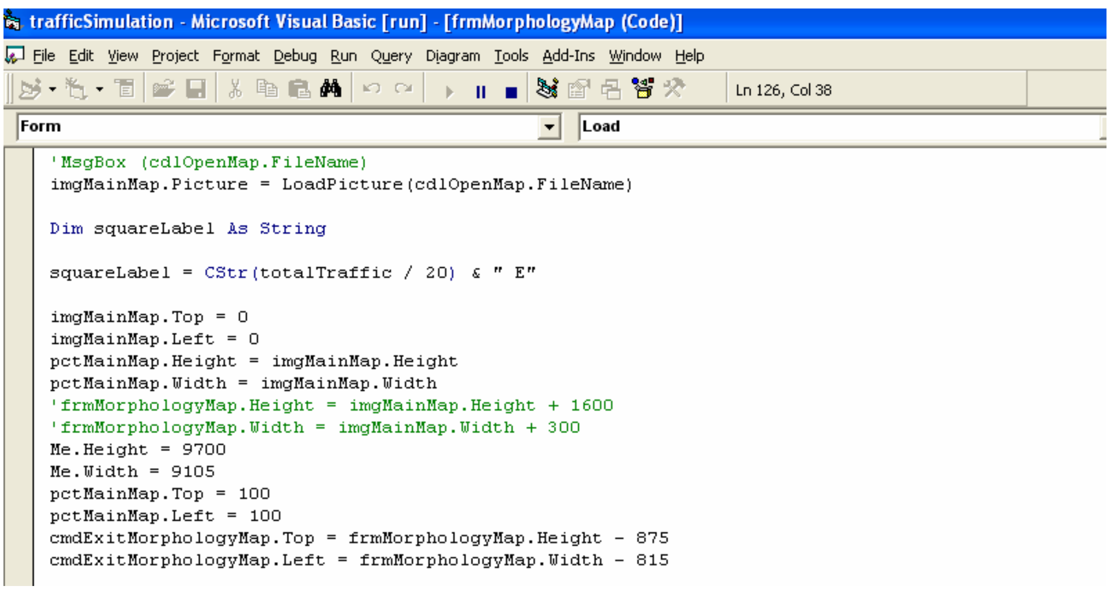
```
Select  ROUND(SUM(ERLANG), 2) AS "ERLANG", TRUNC(SDATE) as “Date”

from XXCELLSTATSBH24

where sdate between to_date('01/12/2003 00:00', 'DD/MM/YYYY HH24:MI')

 and to_date('31/12/2003 00:00', 'DD/MM/YYYY HH24:MI')

and cell in ('24A', '28A', '33B’)

group  BY SDATE, cell

order by cell
```

APPENDIX D: CREATING DATABASE VIEW OF SITES

```
CREATE OR REPLACE VIEW KGLISITES ( BSC, CELL, SITENAME, DTCH, TRU, MAX_ERLANG,
MIN_ERL, AVG_ERL ) AS select cellstats.cell, cellsummary.BSC, cellsummary.Sitename,
round(cellstats.DTCH, 0) DTCH, decode(round(dtch, 0),   5, 1,  6, 1,   7, 1,  13, 2,  14, 2,  19, 3,  21, 3,
22, 3,  23, 3,  29, 4,  30, 4,  37, 5,  45, 6,  null) as tru,

round(avg(cellstats.erlang), 2) AVG_DAILY_ERL, round(max(cellstats.erlang), 2) Max_Erl,
round(min(cellstats.erlang), 2) Min_Erl  from cellstats, cellsummary

where cellsummary.cell=cellstats.cell

and sdate>=sysdate-1  and cellstats. cell in ( '1A', '1C', '2A', '2B', '2C', '3A', '3B', '3C', '4A', '4B', '4C', '5A', '5B',
'5C', '6A', '6B', '6C', '7A', '7B', '7C', '18A', '18B', '18C', '19A', '21A', '21B', '21C', '22A', '22B', '22C', '23A', '23B',
'23C', '24A', '24B', '24C', '25A', '25B', '25C', '26A', '26B', '26C', '27A', '27B', '27C', '28A', '28B', '28C', '29A',
'29B', '29C', '31A', '31B', '31C', '32A', '32B', '32C', '33A', '33B', '38A', '54A', '54B', '54C', '55A', '55B', '55C',
'62A', '62B', '62C')

group by cellsummary.bsc, cellsummary.sitename, cellstats.cell, cellstats.dtch
```

APPENDIX E : GLOBAL VARIABLE IMPLEMENTATION IN T-DET

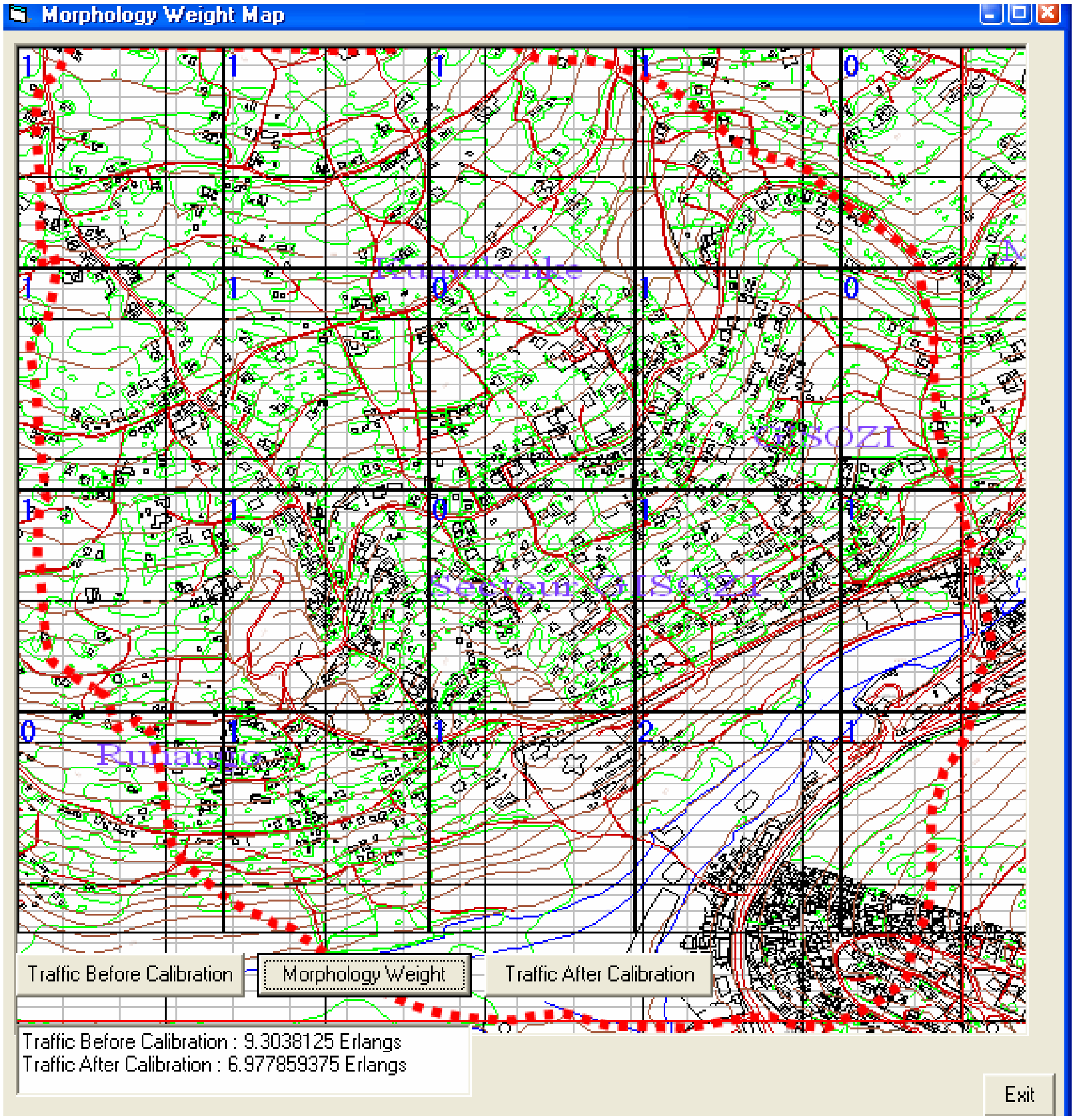




APPENDIX F: IMPLEMENTATION OF THE MAIN MODULE

```
'Define the method

Private Sub cmdCalculateTraffic_Click ( )

On Error GoTo findError

' Capture Variables

areaSurface = txtAreaSurface.Text

popDensity = txtPopulationDensity.Text

penetrationRate = txtPenetrationRate.Text

mEperSubs = txtMEperSubs.Text

' Computation and display

'MsgBox (areaSurface & "--" & popDensity & "--" & penetrationRate & "--" & mEperSubs)

totalPopulation = areaSurface * popDensity

numberSubscribers = (totalPopulation * penetrationRate) / 100

'MsgBox (totalPopulation & "--" & numberSubscribers)

totalTraffic = (numberSubscribers * mEperSubs) / 1000

'MsgBox (totalTraffic & "Erlangs")

txtTotalTraffic = ""

txtTotalTraffic = "Total number of Subscribers : " & numberSubscribers & vbCrLf & "Total Traffic before calibration : " & totalTraffic &
" Erlangs"

' Error Handling routines

findError:

   If Err.Number = 13 Then

   MsgBox ("One of the values you provided is not in a correct format")

   'Resume Next31

   End If

Exit Sub
```

APPENDIX G: IMPLEMENTATION OF WEIGHTING FACTORS IN SUBURBAN RURAL AREA



APPENDIX H: POPULATION FORECASTING

	2000	2005	2010	2015	2020	Evolution 2000 - 2020
Country Category **A**	929	951	970	986	1 000	***8%***
Country Category **B**	446	468	489	509	528	***18%***
Country Category **C**	1 944	2 024	2 102	2 177	2 243	***15%***
Country Category **D**	1 567	1 683	1 795	1 897	1 992	***27%***
Country Category **E**	221	235	250	266	282	***28%***
Country Category **F**	950	1 079	1 220	1 372	1 534	***61%***
Total	**6 057**	**6 441**	**6 826**	**7 207**	**7 579**	***25%***

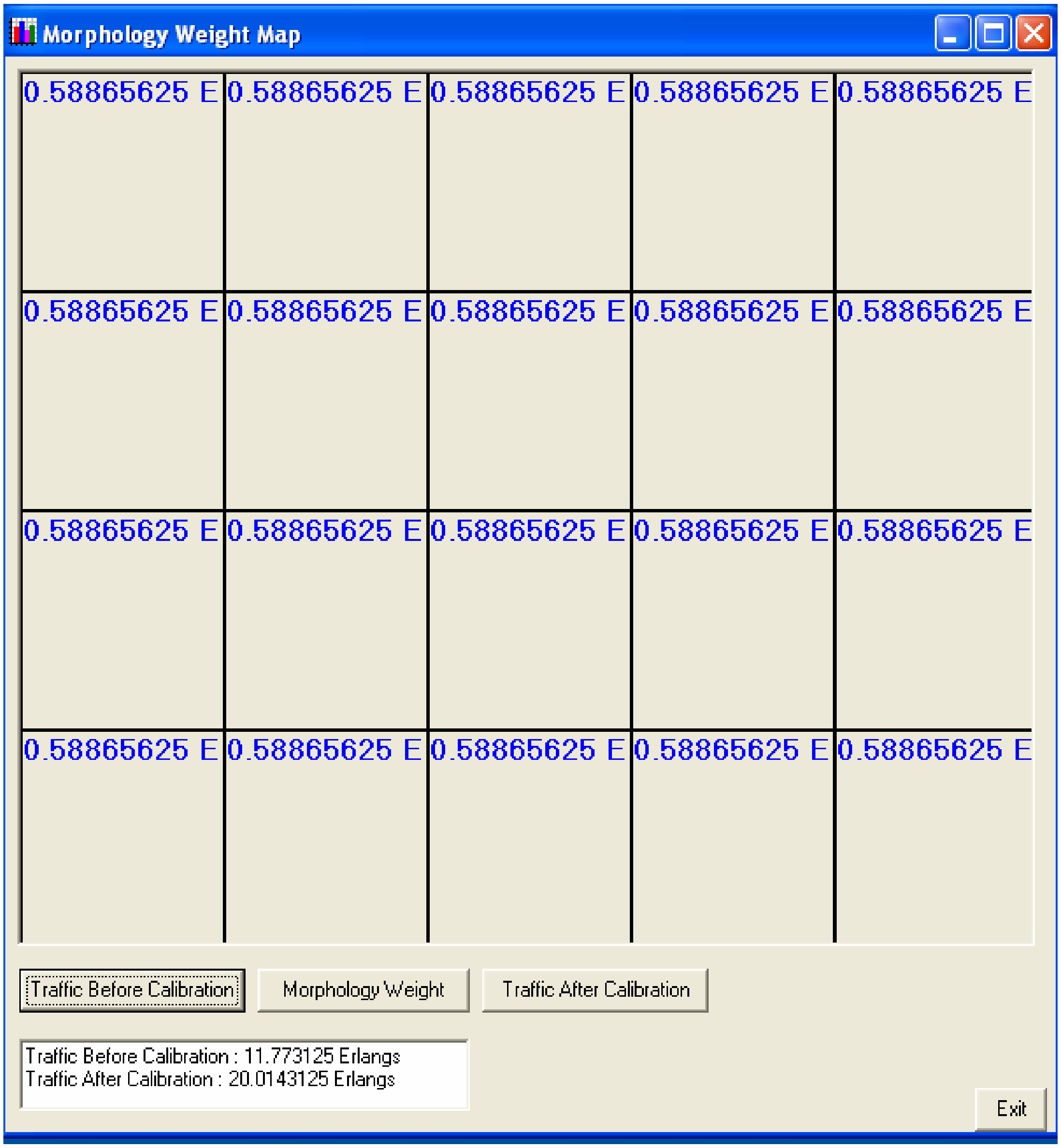
Population forecasts by Country category 2000 – 2020
(Source: *UNO – World Population Prospect – 2001 Revision)*

APPENDIX I: CALCULATION ALGORITHM IMPLEMENTED IN *T-DET*

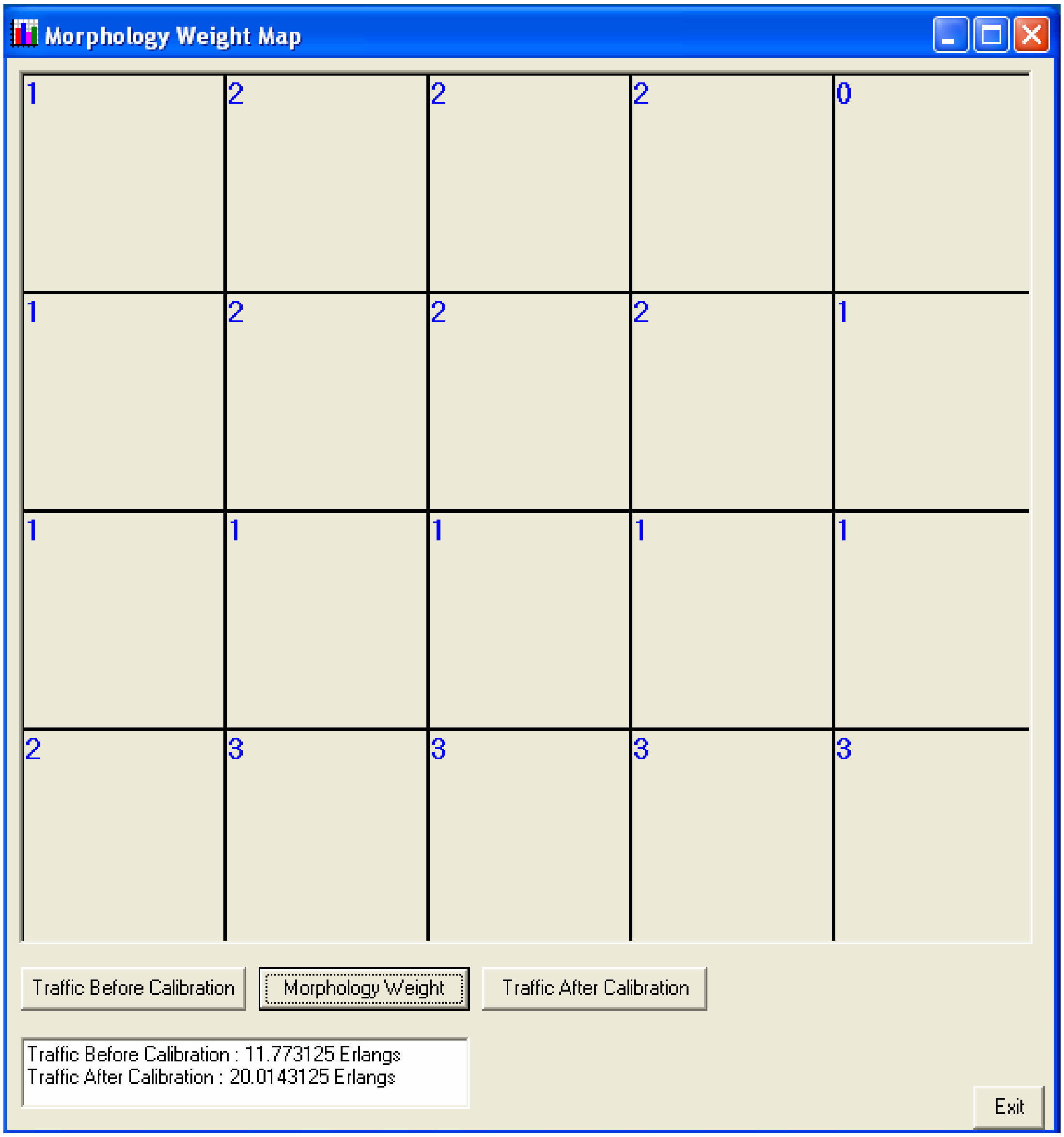
CALCULATING FIRST ORDER TRAFFIC DEMAND P

KEY	INPUT VARIABLE	Source of Data	Method of Collection	Tool(s) Used	Formula /Query	Result/Value
A	Surface Area of km^2	Area bound by a contour drawn around the best server cell	Import of best server coverage into T-DET	ASSET Planning Tool (Aircom Int'l)	Procedure	A=3.080
B	Population Density (Inhabitants/ km^2)	2002 National Census Maps	Direct Capture	n/a	procedure	B=6116
C	No.of People in the Service Area	2002 National Census Maps	Direct Capture	n/a	A*B	C=A.B=18837
D	Service Penetration Rate	CDRLive Database	Query MSSIDN_MAP table, Marketing data	CDRLive Database (LGR Telecoms)	No. of Subs/(A*B)	D=0.025
E	Number of Subs				E= A*B*D	E=471.000
F	Traffic Per Subscriber (Es)	STS ,Marketing data	Direct capture	T-DET	Teletraffic Value (25mE)	Es=0.025
	First order Estimate					11.775

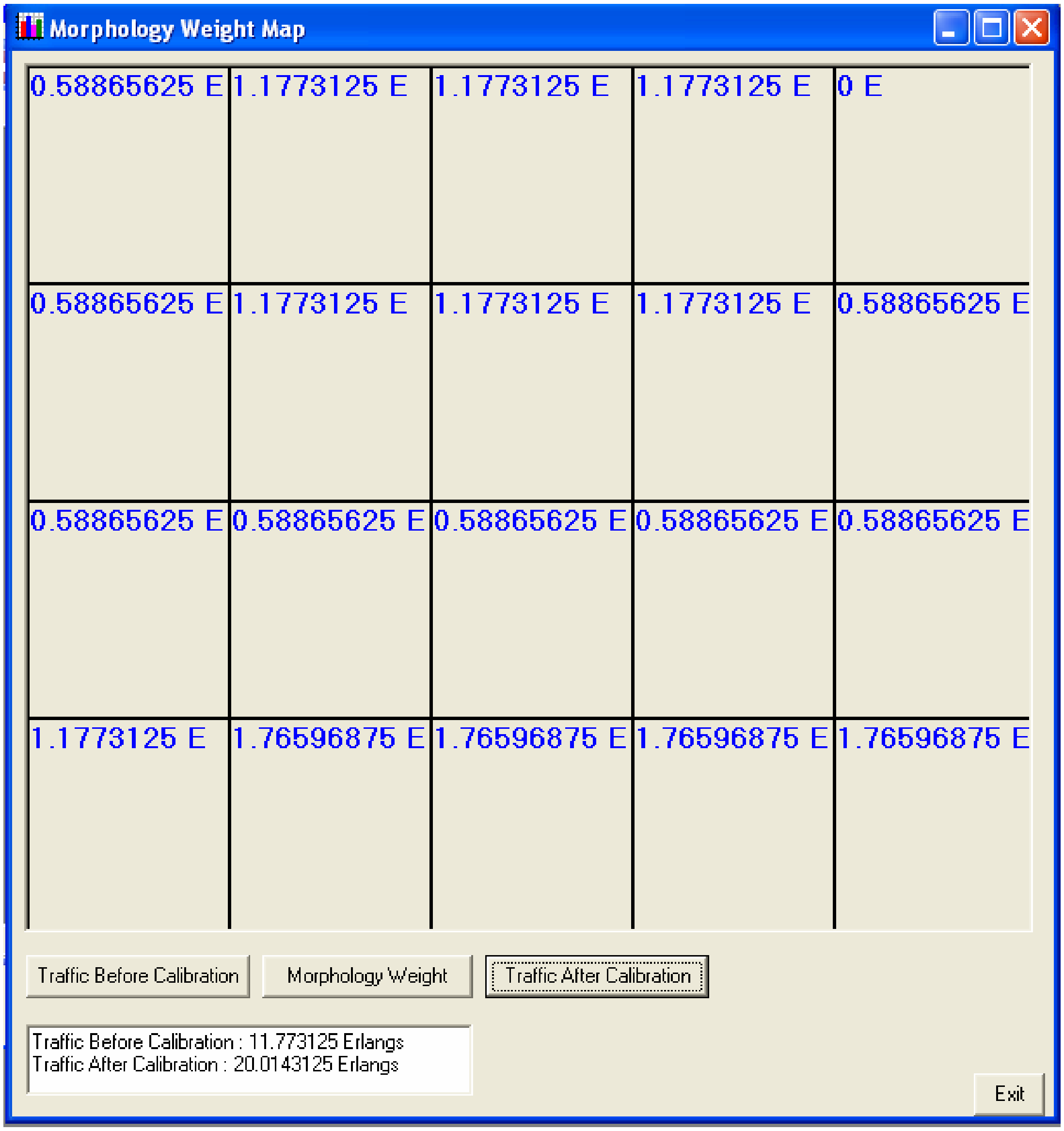
APPENDIX J: TRAFFIC DISTRIBUTION MATRIX IN FIRST ORDER ESTIMATION



APPENDIX K: APPLICATION OF WEIGHTING INDICES



APPENDIX L: SECOND ORDER TRAFFIC DISTRIBUTION MATRIX



APPENDIX M: IMPLEMENTATION OF WEIGHTING FACTORS IN SUBURBAN RESIDENTIAL AREA