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User Mobility Modeling in Cellular Communications Networks

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To all these

who believe in, hope for, and work towards

a more human technology,

I dedicate my work.

Abstract

Mobility management is the cornerstone of cellular philosophy. Mobility analysis gives a deep insight on the impact of the terminal mobility on the cellular system performance. In third-generation mobile communication systems, the influence of mobility on the network performance will be strengthened, mainly due to the huge number of mobile users in conjunction with the small cell size. In particular, the accuracy of mobility modeling becomes essential for the evaluation of system design alternatives and network implementation cost issues. Currently available mobility models tend to be either too simplifying or too sophisticated. For mobility modeling under realistic traffic and environmental conditions, this thesis introduces a novel representation technique which uses the distribution functions of street length, direction changes at crossroads, and terminal velocity. The parameters required, e.g. mean and variance of street length, user velocity, and direction changes distributions, can be easily derived by observation and measurement. Other important factors influenced by user mobility concern the mobile user calling behavior expressed by the incoming/outgoing call arrival rate and average call duration. This work thus brings together teletraffic theory and vehicular traffic theory.

This is capable its to describe the user behavior in detail, and is applied for the characterization of the traffic in individual single cells of the mobile network. The effect of mobility has been analyzed in terms of the local performance measures like *probability of handover* and *call blocking probability* (*for new and handover calls*). Additionally, this model has been used to calculate the *distribution of channel holding times*. The performance of new call handling algorithms are evaluated.

The global performance criteria of interest are *call dropping probability for all calls*, call processing time dependent *forced termination of handovers*, and *channel utilization*. Thus the average number of functions per call for information handling systems with different hierarchical structures can be computed, too.

All these parameters are expressed as a function of the user calling and mobility behavior. To assess the accuracy of the proposed mobility model a simulation tool has been constructed. The tool takes into account the user traffic and mobility behavior over different environments (high density city center, outskirts, etc.). Theoretical results, simulation trials, and measurement data coincide, indicating the excellent accuracy the analytically described mobility model provides.

Additionally, an approach for Space Division Multiple Access (*SDMA*) system modeling is presented. The influence of the different users mobility behavior on key *SDMA* parameters as the time-dependent angle and distance variation between terminal and supported base station, respectively, are explored.

Zusammenfassung

Die Mobilitätsverwaltung ist ein Grundstein des zellulären Konzepts. Die Analyse vom Mobilitätsverhalten der Teilnehmer verschafft uns einen tieferen Blick in die Auswirkung der Endgerätemobilität auf die Systemparameter und Systemeigenschaften. In der dritten Generation von Mobilfunksystemen wird der Einfluß der Mobilität auf das Mobilfunknetz besonders stark ausgeprägt sein, grundsätzlich wegen immer noch steigender Teilnehmerzahlen unter gleichzeitig immer kleiner werdenden Zellgrößen. Die Genauigkeit der Mobilitätsmodellierung gewinnt besonders stark an Bedeutung in Hinsicht auf bessere Auswertung von Planungsalternativen und eine kosteneffektive Netzwerkoptimierung. Die gängigen Mobilitätsmodelle sind entweder zu einfach oder sehr komplex. Für die Mobilitätsmodellierung unter realistischen Verkehrs-, Umgebungs- und Gesprächsverhaltensbedingungen haben wir einen neuen Ansatz entwickelt, der auf die statistische Erfassung der Straßenlänge, der Richtungsänderung an der Kreuzungen und der Teilnehmergeschwindigkeit beruht.

Das vorgeschlagene Mobilitätsmodell hängt von der adäquaten Bestimmung einen Satzes von system- und umgebungsbezogenen Parametern, wie z.B. mittlere Straßenlänge, mittlere Geschwindigkeit und der Varianz der Richtungsänderung, ab. Die Mehrzahl dieser Parameter läßt sich einfach meßtechnisch bestimmen oder ausrechnen.

Eine wichtige Frage der Teilnehmermobilität befaßt sich mit dem Gesprächsverhalten der mobilen Teilnehmer dargestellt durch die Rate ankommender und abgehender Gespräche sowie den mittleren Gesprächsdauer. Deswegen werden in dieser Dissertation die Gesprächs-Verkehrstheorie und Straßen-Verkehrstheorie berücksichtigt und zusammengebracht.

Dank seiner Fähigkeit zur Beschreibung des Teilnehmerverhaltens im Detail wurde das vorgeschlagene Mobilitätsmodell zuerst zur Auswertung des Straßen- und Gesprächsverkehrs in einzelnen Zellen des Mobilfunknetzes eingesetzt. Auf dieser Basis wurde die Wirkung der Mobilität auf die lokalen Systemwerte wie *Handover-Wahrscheinlichkeit* und *Blockierungswahrscheinlichkeit* (*für neue und weitergeführte Gespräche*) analysiert. Weiters wurde das Modell zur Bestimmung der *Kanalbesetztzeit-Statistik* verwendet. Die Leistungsfähigkeit von verschiedenen Algorithmen zur Gesprächsabwicklung wurde ausgewertet.

Die interessanten Qualitätsparameter des Gesamtsystems sind die *Ausfallwahrscheinlichkeit für alle Gespräche*, die von Gesprächsabwicklungzeit abhängige *vorzeitige Gesprächsunterbrechung* und die *Kanalausnutzung*. Damit kann die mittlere Anzahl von Transaktionen auf der Signalisierungsebene für verschiedenen hierarchischen Zellenstrukturen ausgerechnet werden.

Alle diese systemqualitätbestimmenden Parameter sind als Funktionen des Gesprächs- und Mobilitätsverhalten der Teilnehmer dargestellt. Zur Beurteilung der Genauigkeit des von uns vorgestellten Mobilitätsmodells wurde eine Simulationsumgebung entwickelt. Dieses Werkzeug nimmt das Gesprächs- und Mobilitätsverhalten der Teilnehmer in Abhängigkeit von verschiedenen Umgebungsbedingungen (Stadtzentrum, Außenbezirke usw.) in Betracht. Die theoretischen Voraussagen, die Simulationsergebnisse und die gemessenen Daten stimmen überein, was auf eine große Genauigkeit des analytischen Mobilitätsmodells schließen läßt.

Abschließend wurde eine Anwendung zum Modellieren von *SDMA*- (Space Division Multiple Access) Systemen präsentiert. Es wurde der Einfluß des Mobilitätsverhaltens auf die *SDMA*-Schlüsselparameter wie zeitabhängige Winkel- und Abstandsänderung zwischen dem Teilnehmer und der versorgenden Basisstation untersucht.

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***The first** was never to accept anything for true which I did not clearly know to be such; that is to say, carefully to avoid precipitancy and prejudice, and to comprise nothing more in my judgement than what was presented to my mind so clearly and distinctly as to exclude all ground of doubt.*

René Descartes
(DISCOURS DE LA MÉTHODE POUR BIEN CONDUIRE SA RAISON, ET CHERCHER LA VÉRITÉ DANS LES SCIENCES, 1637 - Discourse on the Method for Rightly Conducting One's Reason and Searching for Truth in the Sciences)

Chapter 1

Introduction

1.1 Some Networking Problems in Cellular Systems

One of the main features that cellular mobile networks exhibit is the ability to deal with moving terminals. As movement may imply a change of access port, network control functions unique to this kind of communication system are required. In general, the network has to deal with *terminal mobility*, a task often referred to as *mobility management*. Another form of mobility is *personal mobility*, whereby the user can make use of services irrespective of his point of attachment to the network or specific terminal. A terminal or mobile station may be moving while it is engaged in a communication context (i.e., a connection or data session) or while it is in an idle state. *Service mobility* is needed to integrate and manage the multiple media (e.g., voice, voice mail, electronic mail, data, fax, paging, and video) that will be used to reach subscribers. Since each user's needs are unique, the network must store, maintain, and update customer profiles which describe preferred services, features, and means of delivery by time of day and day of week.

Handover, whereby the mobile station changes its current access port or base station during a connection, is probably the most obvious and explored mobility management procedure. To ensure the continuity of an already initiated connection, the mobile station is "handed over" between the access ports involved. However, when a mobile station is not engaged in a communication context, the network must be able to determine its current cell in order to set-up and route properly an incoming connection (a so-called mobile-terminated connection). *Location management* is concerned with the issues of tracking and finding the mobile stations in order to allow roaming within the network coverage area. On the radio link between base stations and mobile terminals, two basic operations can be distinguished: *paging* and *location updating*. Paging refers to that procedure whereby the network searches for the exact access port(s) through which a mobile station can be reached. Location updating refers to that procedure whereby the mobile terminal informs the network about its current location by means of some trigger, so an exhaustive search through all possible base stations can be avoided. Both operations are resource-consuming, since both of them involve (radio) signaling.

Both personal and terminal mobility create tremendous new problems for telecommunication networks since it is no longer well known to the network where (potential) users are. The development of realistic, measurement-based and possibly place- and time-dependent mobility models of users (both en masse and as individuals) would greatly facilitate the design of cost-efficient networks that meet customer demands.

1.1.1 Evolution of Wireless Communication Networks

One of the most challenging aspects of wireless communications systems is the need to develop engineering solutions that span a large range of considerations, from integrated circuits to radio engineering to system software. To make progress in wireless systems, a more interdisciplinary approach that cuts across the traditional disciplines of circuit design, signal processing, radio engineering, network design, and computer system design will be needed. As mentioned earlier, the key cross-cutting consideration in wireless design is that mobility implies adaptability in the system's architecture and algorithms.

Today's cellular networks now provide service to customers using mobile terminals through the use of advanced wireless technologies. As these technologies mature and are coupled with greater intelligence in the network, the ability to roam around the globe and communicate through handheld terminals with high quality of service (*QoS*) will become reality. The most obvious technological innovations that will be required in wireless communications are in the areas of increasing the efficiency spectrum of radio transmission and increasing radio channel capacity. However, significant additional technological innovations are also required in the fixed network to support the anticipated high-mobility, high-density, multimedia environment of the future. Extensive new signaling demands will be placed on these networks, requiring significant innovations in intelligent network technology, signaling protocols, and database systems.

Teletraffic engineers must create new models of the spatial and temporal volatility inherent in terminal mobility in order to properly size future network resources and enable the delivery of high-quality services. New strategies for managing handovers as the sizes of cells in mobile networks shrink are needed. New power control algorithms that maximize capacity while maintaining high quality are important. Due to the interacting factors of the technology and service innovations with the business drivers and the lack of mature teletraffic modeling techniques, engineering practices in wireless networks have often led to uneven *QoS*.

Teletraffic engineers must not only be able to grapple with the new traffic generated by the wireless application (e.g., signaling from handovers, location updates, and authentication), but also determine which of the numerous parameter dependencies are important and then devise methods for incorporating these into simple representative models. Some of the possible candidates for such dependencies include time, density, velocity, calling rate, call holding time, and cell/location area and geometry. Methods for choosing appropriate models that fit a wide spectrum of measured data are therefore needed.

The design of third generation mobile communication networks faces three major challenges: first, there is the tremendous word wide increase in the demand for mobile communications services. Second, the main resource in wireless systems, i.e. the frequency spectrum, is extremely limited. And third, new access technologies like *Space Division Multiple Access* (*SDMA*) and *Code Division Multiple Access* (*CDMA*) require new mobile network planning methods. Since these challenges are strongly interconnected, they can only be addressed by an integrated user mobility and teletraffic concept, in order to obtain an efficient, economic and optimal mobile network configuration.

Third generation mobile systems are in the process of being specified by *ITU* and *ETSI*, as *IMT2000* (*International Mobile Telecommunications 2000*) and *UMTS* (*Universal Mobile Telecommunications System*), respectively. *UMTS* will take the personal communications user into the information society of the 21st century [UMT97], [UMT98]. It will deliver information directly to people and provide them with access to new and interactive services. It will offer mobile personalized communications to the mass market regardless of location, network or terminal used. People spend more time on the move and want to communicate and be informed when traveling. *UMTS* needs to respond to the demand of consumers, who want to combine mobility with multimedia applications.

The general trend foreseen for *UMTS* (dense cellular layout, variety of services and environments with several traffic and mobility levels) will increase the control capacity requirements. In this context it is important to model all the basic process, namely those related to the traffic management (e.g., call control) and those driving the mobility process. The latter can be further distinguished between "call related" (handover) and "call unrelated" (location updating). The overall behavior of the mobile user must then be characterized through a suitable representation of its traffic (rate of calls and duration) and mobility (e.g., velocity, direction) attitude. In particular, it is important to model the rate of generation of the related signaling procedures.

1.1.2 Mobility and Traffic Modeling

Cellular systems must deliver a variety of services to many types of users having a wide range of mobility characteristics. The envisioned systems and the services they will provide (voice, data, e-mail, etc.) are sometimes difficult to model. Much of the difficulty in developing analytically tractable models arises from the mobility of the network users, especially the handovers required by such users. The effects of user mobility on system performance are a central issue for the design and implementation of mobile networks.

The development of analytically tractable models to compute teletraffic performance characteristics of mobile wireless networks has been the thrust of this work. An essential feature is the characterization of user mobility by a *sojourn* or *dwell time*. The sojourn time of a user is defined as a random variable that gives the amount of time that a user can maintain a satisfactory two-way communication link with a given network gateway. A user's sojourn time depends on many factors, including speed, path, transmitting power, signal propagation, and interference. Mobility models are necessary for the analysis of many additional pertinent cellular issues. Some of these include signaling load associated user location and handover initiation algorithms.

The recent wireless networks have small cells, which lead to smaller mean sojourn time for users traversing the system. Also, since the transmitting power is reduced, obstacles such as buildings, trees, hills, etc. will have a greater effect on cell size and shape. The result is that cells tend to be less regular in shape and more variable throughout the coverage area. This large variation in cell size and shape, together with the shorter mean sojourn time, suggest consideration of mobility models which considers both the heterogeneity of the street system (the environment) and the subscriber units (pedestrians, cars), Fig. 1.1.

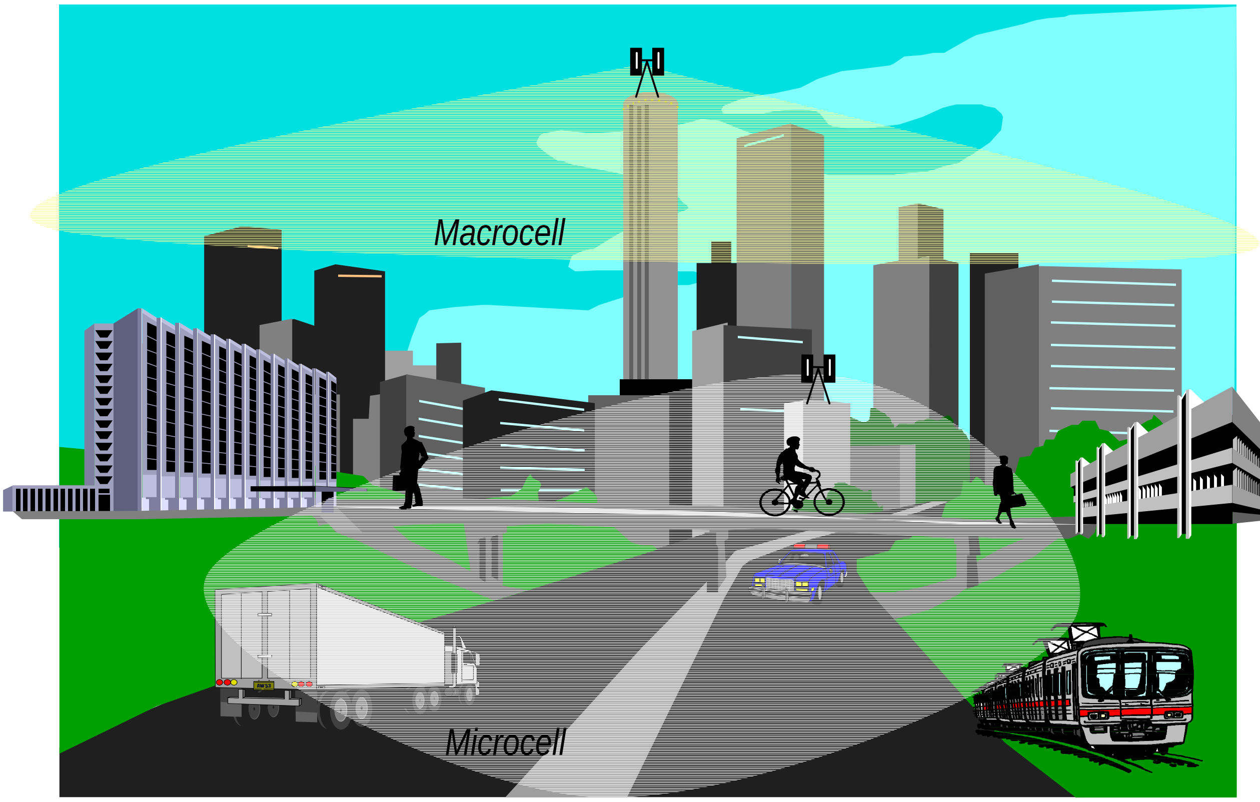


Figure 1.1 **:** Hierarchical cellular mobile communication system.

In mobile communications, service provision to mobile users is accomplished by:

- Location management procedures (location update, domain update, user registration, user location, etc.), used to keep track of the user/terminal location.
- The handover procedure, which allows for the continuity of ongoing calls.

The performance of the above procedures is influenced by the user mobility behavior. Their application directly affects:

- The signaling load generated on both the radio link and the fixed network (e.g., location updating rate, paging signaling load).
- The database queries load.

Additionally, the handover procedure affects the offered traffic volume per cell as well as the quality of service (*QoS*) experienced by the mobile subscriber (e.g., call dropping). In wireless telecommunication systems, the estimation of the above parameters, which are critical for network planing and system design (e.g., location and paging area planning, handover strategies, channel assignment schemes), urge for the development of "appropriate" mobility models. Due to diversification of the above issues, different mobility detail levels are required, such as the following (Fig. 1.2):

a)

b)

c)

Figure 1.2 : The required three different mobility detail levels.

***a*) Location Management Aspects** - Location area planning, multiple-step paging strategies, data location strategies, database query load. Location-management-related issues require the knowledge of the user location with an accuracy of a large-scale area (e.g., location or paging area).

***b*) Radio Resource Management Aspects** - Cell layout, channel allocation schemes (fixed/direct channel allocation, *FCA*/*DCA*), multiple access techniques (time-division/ frequency-division /code-division, *TDMA*/*FDMA*/*CDMA*), system capacity estimation, *QoS*-related aspects, signaling and traffic load estimation, user calling patterns. Radio-resource-management-related aspects require medium-scale area accuracy (e.g., cell area).

***c*) Radio Propagation Aspects** - Signal strength variation, time dispersion, interference level (co-channel and adjacent channel interference) handover decision algorithm (based on the signal strength variation). The analysis of radio propagation aspects needs accuracy of a small-scale area.

1.3 Statement of the Problem

The teletraffic modeling, engineering, and management has reached a whole new dimension with the once unforeseen growth and scope of personal communication services, making use of multiple technologies and infrastructures. Teletraffic problems have evolved as rapidly as personal communications. The scarcity of spectrum and the separation of call and connection management gave rise to a whole new family of fixed and dynamic resource allocation techniques. Mobility, tracking, and quality-related functions raise new questions. Consequently, there is an impetus to understand the mobility and its effect on communication systems. However, *individual* mobility is not yet fully understood and still being modeled in very roughly and insufficient ways under unrealistic assumptions.

This dissertation is an attempt to construct a comprehensive model for user mobility and traffic with the objective of evaluating and devising strategies for channel assignment (for new and handover calls) in *multilayer wireless cellular* systems, and designs for information handling architectures. The desired model must consider both the heterogeneity of the traffic (e.g., street pattern, building environment, vehicular-traffic rules) systems and the subscriber units, respectively. The easily application of this mobility model in real network planning cases must be guaranteed.

Due to their capability to describe the user behavior in detail, the proposed mobility model can be applied for the characterization of the traffic in an individual single cell of a mobile network. Based on this model, the effect of mobility is analyzed in terms of the locale performance measures like *probability of performing a handover* and *call blocking probability* (*for new and handover calls*). Additionally, this model can be used to calculate the *distribution of channel holding times*. The performance of new call handling algorithms are evaluated.

The global performance criteria of interest are *call dropping probability for all calls*, call processing time dependent *forced termination for handovers*, and *channel utilization*. Thus the average number of functions per call for information handling systems with different hierarchical structures can be computed, too.

1.4 Overview of the Dissertation

In Chapter 2, first are described the existing traffic source models used so far in mobile network design. Subsequently, a novel mobility model for the subscriber units is introduced, focusing on the traffic in a given cell under realistic traffic conditions. Calls can be initiated anywhere within the cell. The motion of subscriber units is modeled by introducing distribution functions of street length, direction changes at crossroads, and subscriber unit velocity.

In Chapter 3, the mobile user calling behavior is discussed. Then, the mobility model is used to characterize different mobility-related traffic parameters in cellular systems. These include the distribution of the cell sojourn time of both new and handover calls. The probability of handover is thereby obtained and the channel holding time is measured.

Chapters 4 outlines how the mobility model developed in Chapter 2 can be used for performance evaluation of channel assignment methods for handovers and heterogeneous users. Probabilities of blocking for the different classes of users are computer. Additionally, an approach for *SDMA* system modeling is presented. The influence of the different users mobility behavior on key *SDMA* parameters as the time-dependent angle and distance variation between terminal and supported base station, respectively, are explored.

The last two sections summarize the presented work and give a outlook for further work.

Part I

Mobility and Traffic Modeling

> ***The second****, to divide each of the difficulties under examination into as many parts as possible, and as might be necessary for its adequate solution.*
>
> ***René Descartes***
> *(DISCOURS DE LA MÉTHODE POUR BIEN CONDUIRE SA RAISON, ET CHERCHER LA VÉRITÉ DANS LES SCIENCES, 1637 - Discourse on the Method for Rightly Conducting One's Reason and Searching for Truth in the Sciences)*

Chapter 2

Modeling the Mobility of Cellular Traffic Sources

2.1 Introduction

In recent mobile communication systems, the influence of the mobility on the network performance (e.g., handover rate) will be strengthened, mainly due huge number of mobile users in conjunction with the small cell size. In particular, the accuracy of mobility models becomes essential for the evaluation of system design alternatives and network implementation cost issues.

2.1.1 Mobility and Traffic Behavior of Mobile Users

The primary task of mobile system planning is to locate and configure the facilities, i.e. the base stations or the switching centers, and to interconnect them in an optimal way. To achieve an efficient and economic system configuration, the design of a mobile network has to be based on the analysis of the distribution of the expected teletraffic demand in complete service area. In contrast, the teletraffic models applied so far for the demand estimation, characterize the teletraffic only in a single cell or single user and they are too complex for practical use in the planning process. Therefore, the demand based design of mobile communication systems requires a traffic estimation and characterization procedure which is simple as well as accurate.

The offered traffic in a region can be estimated by the geographical and demographical characteristics of the service area. Such a demand model relates factors like *land use*, *population density*, *vehicular traffic*, and *income per capita* with the calling behavior of the mobile units.

Taking into account the requirements relevant to mobile communications, two kinds of modeling techniques are defined:

- A *mobility model*, modeling the mobility behavior of the users, in terms of for example user speed and typical density of users in a specific geographical area.
- A *call or teletraffic model*, modeling the possible call cases, where calls are divided into categories as mobile-to-fixed/mobile-to-mobile, business/residential etc. as these properties may have impact on the call arrival rate, call duration etc.

These two models thus bring together a robustly methodology to study wireless networks [Lam97], [Wir97].

In order to analyze and model various scenarios of user mobility and traffic we first divide the traffic in different user classes (in Chapter 3.2 is presented a detailed description). Each user class is assigned at least one mobility model. Using the principle of combining user classes, various realistic scenarios can be studied and modeled with an arbitrary grade of accuracy.

2.1.2 Overview of the Transportation Theory

Transportation theory aims at the analysis and design of transportation systems (e.g., railways, street networks). The basic issue the transportation theory attempts to resolve is the following: "*Given a transportation system serving a certain geographical area, determine the load this system should carry*". The input framework utilized as a basic for the development of the relevant models is described by the following items.

Trips - A trip (movement) is characterized by:

- The purpose,
- The end points (origin-destination),
- The transportation means utilized,
- The route followed.

Given a certain geographical area, a trip can be characterized according to its end points' locations as:

- Internal (both end points inside the area),
- Outgoing (origination inside the area, destination outside),
- Incoming (the opposite of outgoing),
- External (both end points outside the area).

Area Zones - Transportation theory divides the geographical area under study into area zones. The division is based on criteria related to:

- Population density,
- Natural limits (e.g., rivers, parks, highways, railway tracks).

Note that the trip end points are considered with area zone accuracy.

Population Groups - The population of the area under study is divided into groups according to their mobility characteristics. Examples are working people, residential users, and tourists. An example is shown in Fig. 2.1 [Mar97].

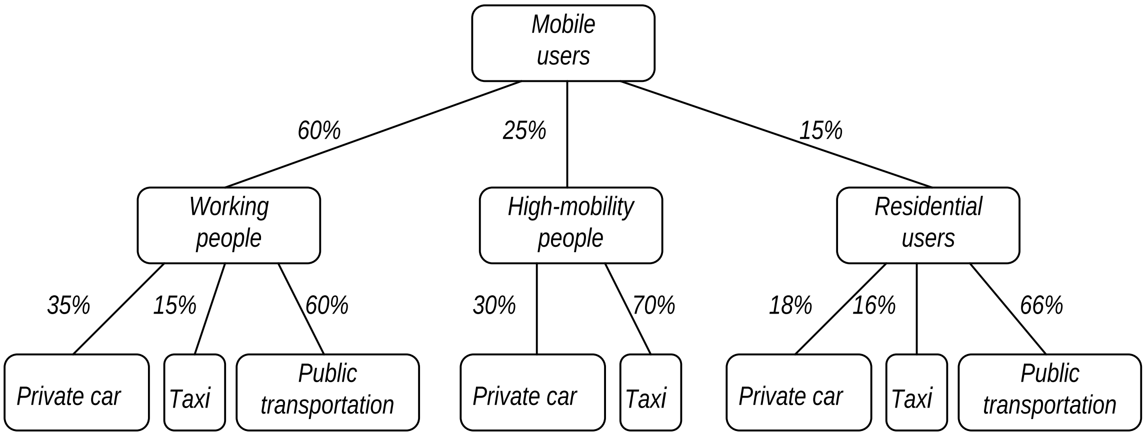


Figure 2.1 : Categorization of mobile users according to their mobility behavior.

Movement Attraction Points - Movement represent locations that attract population movements and at which people spend considerable time periods. Examples are workplaces, residences, and shopping centers. Each movement attraction point characterizes the population group it attracts. Figure 2._ presents the distribution of movement attraction points over the whole area of a typical European capital [Mar97].

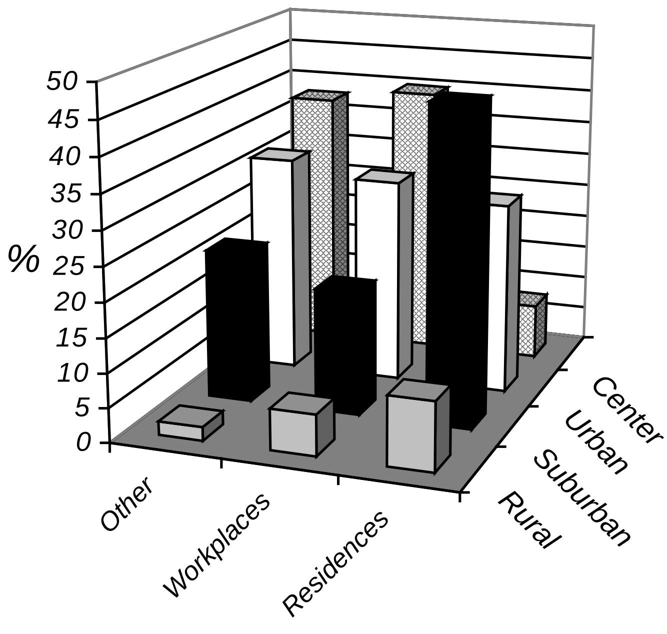


Figure 2.2 : The distribution of movement attraction points over the city area.

Time Zones - During a day, it can be observed that there are time periods during which certain types of movements take place (e.g., movements toward workplaces) and time periods where certain population groups reside at certain movement attraction points (e.g., working hours, shopping hours). These time periods are called *time zones*. Transportation theory concentrates on the so-called rush hours, where the peak load occurs on the transportation system under study.

Transportation System Characteristics - A transportation system (e.g., a street network, an urban bus network, the subway) is characterized by:

- Its capacity,
- The trips it may support,
- The usage cost measured in terms of time and money.

The basic models used by the transportation theory are:

Trip Production and Attraction Models - The output parameters of these models are the number of trips produced and attracted by each area zone. An example is the "regression model" [Woo67].

Trip Distribution Models - The output of these models is the so-called origination-destination matrix $\boldsymbol{OD}(A_i, A_j)$. Each element of this matrix equals the number of trips originated from area zone A_i and destined to area zone A_j. An example is the "gravity model" [Eva73].

Modal Split Models - The output of these models is the transportation means an individual selects to perform a trip with given end points. The major parameters considered here are user annual income and transportation usage cost.

Vehicular Traffic Assignment Models - These models are used for the estimation of the probability a certain route is selected, given the trip end points and the street network [Leb75]. The criteria utilized here are the route length and usage cost.

The primary aim of this thesis was the development of a mobility model that would incorporate map information and vehicle dynamics. Empirical information sources complement the processes involved in incorporating the secondary information. In the following a range of empirical information sources, by no means an exhaustive list, are described. Initially they are classified according to their source but they will eventually be modeled according to the properties of the information rather than the source.

A. Map Attributes

Paper based road maps, currently the most widely available form of road network information, have many attributes associated with the road network; for example, road type, weight limits, traffic lights. Digital road map standards allow for the incorporation of such attributes.

Road Type Classification - The road type classification, for example arterial road, main road, and suburban street, is an indication of the amount of traffic likely to be found on a given road. The implication for any given vehicle is that it is more likely to be found on an arterial road compared to a nearby suburban street parallel to that arterial road.

Road Rules - Road rules are well documented and although road rules do not define where motor vehicles are more likely to be found they do indicate that certain actions are less likely to occur; for example, a right hand turn contrary to a No Right Hand Turn restriction. The majority of the driving public obey the rules of the road and, as such, any hypothesized vehicle trajectory that appears to transgress a road rule is less likely to be the correct one. That is, road rules restrict (reduce the likelihood of) certain actions. Many of these rules are also soft in that they generally do not prevent actions but rely on drivers to obey the rules. In the following are described how some road rules can be used to aid position estimation.

- ***Speed Limits*** - The speed limit of a given road can be used as an indicator of the likelihood of a hypothesized trajectory travelling along that road. For example, if the estimated vehicle speed is significantly greater than the speed limit then the hypothesized trajectory is less likely, again assuming that drivers are law abiding citizens. The converse is not necessarily true as factors such as traffic congestion, driver choice, and vehicle performance limitations can mean that the vehicle's speed will be lower than the posted speed limit. One particular scenario where speed can be used to differentiate which road a vehicle is on occurs when there is an urban street parallel to a freeway. There will be a significant difference between the posted speed limits for each of these roads. If the vehicle is travelling at a speed significantly greater than the urban speed limit, then it is more likely that the vehicle is on the freeway**.** A vehicle speed nearer that of the urban speed limit does not necessarily imply that the vehicle is on the urban road and not the freeway as traffic conditions could be forcing a lower speed on the freeway.
- ***Route Restrictions*** - Apart from the advantages for route guidance, such data also represents a source of moving behavior information. There are number of road rules that place soft limitations on travelling certain routes. *No Right Turns*, *No Left Turns*, *No U-Turn*, and *One-Way Streets* do not prevent a driver from turning right or travelling the wrong way down a one-way street and as such they represent "soft" information. The majority of citizens are law abiding and therefore a hypothesized trajectory that indicates that a vehicle has broken a road rule is much less likely.
- ***Vehicular Restrictions*** - The movements of certain vehicles is also hard and soft limited by factors such as weight, height, width and length. Road and bridges can have weight restrictions imposed upon them to avoid excessive damage due to heavy vehicles. There is nothing physically preventing "heavy" vehicles from travelling over such roads and hence the restriction is "soft". Similarly, there are also restrictions for long and wide vehicles.
- ***Forced Maneuvers*** - Forced maneuvers refers to deceleration maneuvers forced by road rules. A vehicle encountering a *Stop* or *Give Way* sign at an intersection has to slow down and be prepared to give way to other vehicles that have right of way as defined by the road rules. A hypothesized trajectory that shows a vehicle going through a *Stop* or *Give Way* without slowing down represents a trajectory that indicates that the driver has broken the law and that the driver has exposed him/herself to a dangerous situation. Again there is nothing physically forcing the driver to stop or slow down and thus the information is "soft" but such an action reduces the likelihood of the hypothesis that indicates the violation of the road rule. Conversely, if a vehicle significantly slows down approaching an intersection where it is expected to have right of way tends to indicate against straight ahead travel. The vehicle would only be likely to appreciably slow down if the driver was planning to turn left or right.

Physical Restrictions - Turning against a *No Right Turn* at an intersection or travelling the wrong way down one-way streets represent violations of road rules. Such actions represent "soft" information; there is nothing physically enforcing the road rules. There are also hard limitations which cannot be violated as easily. Some freeways are divided by physical barriers preventing wrong way travel and U-turns and similarly median strips and crash barriers can physically prevent U-turns and right-hand turns. Intersections can also be constructed such that all traffic is forced to turn a certain direction; "*All Vehicles Must Turn Left*" for example. That is, straight ahead travel is prevented by some physical barrier.

B. Predetermined and Observed Behaviors

Some aspects of driver/vehicle behavior are predetermined. If an hypothesized action that implies or represents behavior contrary to predetermined norms then that hypothesis is less likely to be correct. One example of predetermined vehicle behavior is the fixed routes allocated to public transport buses, both urban and interurban. Another example is the fitting of speed governors to heavy vehicles thus physically limiting their speed. Empirical information concerning the movement of vehicles can be used to predict where a vehicle is more likely to be found or what action a vehicle is more likely to take. Two sources of such information have been identified: traffic flow information describing gross vehicle behavior and detailed historical information on the movements of a given vehicle and/or driver.

Fixed (Predetermined) Routes - Public transport buses are restricted to predetermined routes; deviations arising only in special circumstances such as a driver new to the route getting lost, road works, special events or motor vehicle accidents necessitating a detour. Hypotheses that indicate a bus leaving its predetermined route are unlikely to be correct. It could be argued that such hypotheses should be deleted immediately but this results in the loss of all alternate hypotheses which could be valid in certain exceptional circumstances such as those listed above. In this respect, hypotheses that diverge from the specified route are similar to drivers who violate turn restrictions. There is no physical enforcement, just a high probability that the contra-indicated action has not been undertaken.

Speed Governors - Some vehicles, in particular heavy vehicles, are fitted with speed governors which physically limit the speed of a vehicle. Although such devices can be tampered with, they represent a source of information similar to speed limits. That is a hypothesis with a current speed significantly in excess of the governed limit is less likely to be the correct hypothesis.

Traffic Flow Data - Traffic flow information is an improvement on road type classifications. Traffic control authorities, local councils, etc., collect data on the amount of traffic flowing on different roads at different times of the day and variations according to the day of the week. While this information may change over time, it is relatively static and could be used as an indication of which road or roads a vehicle is more likely to be on.

Driver Behavior - Capturing driver and/or vehicle behavior generates valuable information concerning the likely position of motor vehicles. Many vehicular journeys are repeatable; people drive to and from their place of work, to and from friends and relatives, to and from the shopping center, etc.; couriers often have a set of regular clients; public transport vehicles have fixed routes. Some of these journeys can even be predicted by the time of day and day of the week. If this a *priori* information were available then it would be possible to more accurately position a vehicle. Past position estimates are logged to form a history of vehicle movements for a given driver and/or vehicle depending on which is the more repeatable; a given driver may use a fleet vehicle but visit a number of known clients or conversely a vehicle may follow one of a number of routes independent of the driver (e.g., public transport buses). The current journey could be matched to the recorded journeys to find similar journeys in the past. It would then be possible to bias the selection of the best hypothesis according to the likelihood of a given action according to past behavior. Logging driver/vehicle behavior also inherently captures a number of other empirical information sources. Many road rules are detected through the behavior of the driver. No right turns, one-way streets, etc. are evidenced by the lack of events contrary to the given sign. This is not to imply that the lack of an observed action means that there is a restrictive road sign, rather that the observed driver behavior inherently captures this information source. Similarly if a given driver is not particularly law-abiding, then the occasional breach of restrictive road signs will also be captured and subsequently added to the history of the driver's behavior. If the time-of-day and day-of-week also form part of the pattern being matched then road signs that vary with the time-of-day and day-of-week are also inherently captured.

2.2 Previous Mobility Models

Before discussing the mobility model which have been developed, we first review some common approaches for modeling human movements. Several mobility modeling approaches (simulation and analytical) can be found in the literature. Analytical models, based on simplifying assumptions, may provide useful conclusions regarding critical network dimensioning parameters. Studies on more realistic analytical models indicate that closed form solutions can be derived for simple cases only (e.g., highways at free flow, regular cell shapes, etc.). On the other hand, computer simulation studies consider more detailed and realistic mobility models. Among the disadvantages of these models are the amount of required input parameters, the verification of results vs. real measurements, and the required computational effort.

2.2.1 Fluid Model

The fluid model [Tho88], [Fro94], [Leu94] conceptualizes traffic flow as the flow of a fluid. It is used to model macroscopic movement behavior. In its simplest form, the model formulates the amount of traffic flowing out of a region to be proportional to the population density within the region, the average velocity, and the length of the region boundary. For a circular region with a population density of ρ, an average velocity of $\bar{v}$, and region circumference of L, the average number of site crossings per unit time, N, is

$$N = \frac{\rho \bar{v} L}{\pi} \ . \tag{2.1}$$

This formula is appealing in its simplicity since it is valid for an arbitrary cell shape. In [Ses92] it is shown that this model is reasonable for a Manhattan grid of streets, but becomes inaccurate as the layout of streets becomes irregular. This is because of the assumption of uniform movement with respect to the boundary does not hold for irregular layouts. In order to apply Eq. 2.1 the correct relation between the user density and velocity must be used. For example, we all know that during a traffic jam vehicular traffic comes to a halt. Relationships between density and velocity can be found in [May90].

A more sophisticated fluid model can be also formulated by characterizing the flow of traffic as a diffusion process [Ros96]. One of the limitations of the fluid model is that it describes aggregate traffic and therefore is hard to apply to situations where individual movement patterns are desired, for example, when evaluating networks protocols or data management schemes with caching. Another limitation comes from the fact that since average velocity are used, this model is more accurate for regions containing a large population, such as the case in [Lo92].

2.2.2 Markovian Model

The Markovian model [Bar94], also known as the random-walk model, describes individual movement behavior. In this model, subscriber will either remain within a region or move to an adjacent region according to a transition probability distribution. One of the limitations of this approach is that there is not concept of trips or consecutive movements through a series of regions.

Other mobility models rely on Brownian motion space increments [Tek94]. The principal aim of this methodology is to avoid restrictions on the motion, so that the mobile could both start and change its direction anywhere and anytime. The mobile is randomly assigned an initial direction φ and a speed v, where φ is uniformly distributed, and v is normally distributed as

$$pdf(v) = \frac{1}{\sigma_v \sqrt{2\pi}} \exp\left(-\frac{\left(v - \bar{v}\right)^2}{2\sigma_v^2} \right) , \tag{2.2}$$

with mean velocity $\bar{v}$ which can be chosen e.g. as the speed limit of the modeled area and some variance σ_v. Although the model can be considered usable in the case of pedestrian subscribers, in the case of vehicular motion, subscribers are street bound and speed regulated. This imposes restrictions that are not accounted for by the simple Brownian modeling.

2.2.3 Gravity Model

Gravity models have been used extensively in transportation research to model human movement behavior. They have been applied to regions of varying sizes, from city models [Ben71], [Bou65] to national and international models [Sla93]. There are many variations among the gravity models, and it is not possible to describe all of them here. In its simplest form, the amount of traffic $T_{i,j}$ moving from region i to region j is described by:

$$T_{i,j}=K_{i,j}P_iP_j \tag{2.3}$$

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 $K_{i,j}$. For example, analogous to Newton's gravitational law, $K_{i,j}$ can be specified to have inverse square dependence between zones i and j.

As suggested by Eq. 2.3, the model describes aggregate traffic and therefore suffers from some of the same limitations as the fluid model. However, if we interpret P_i as the "attractivity" of region i and $T_{i,j}$ as the probability of movements between i and j, we can use the model to describe individual movement behavior. Using this approach, the parameters $\{T_{i,j}\}$ also have to be calculated from the traffic data in addition to $\{K_{i,j}\}$. The advantage of the gravity model is that frequently visited locations can be modeled easily since they are simply regions with large attractivity. The main difficulty with applying the gravity model is that many parameters have to be calculated and it is therefore hard to model a geography with many regions.

Pattern recognition techniques based on hidden Markov models [Ken95], which are applied to *GSM* measurement data, have been shown to be appropriate for the determination of the mobile station's location. For computational reasons this is so far limited to a certain number of location in the road network.

2.2.4 Mobility Tracing

A more accurate modeling of the microscopic mobility behavior of users in urban areas is allowed through mobile trace launching. The mobility tracing models can be derived directly from the mobility pattern. The application of these models in real network planing cases is strongly limited. Some models, like [Ses92] or [Mar97] give a deep insight on the impact of terminal mobility on cellular system performance, however they are rather complex to be applied in real network design. Other models, like [Ben92], due to their simplification assumptions, can only be applied for the determination of the parameters in an isolated regular (e.g., rectangular) cell.

Due to their capability to describe the user mobility behavior in detail, we focus in following in greater detail on this type of modeling.

2.2.4.1 Street Pattern Tracing

The mobile is allowed to move on a predefined stretch only, which models e.g. a highway or a main street where directions changes are very unlikely to occur. For the ease of simulation, those streets can be represented by a polygon set of consecutive straight lines. In this model just the speed v of the mobile is chosen randomly (from a uniform or normal distribution) whilst the direction φ is given by the position of the mobile within the stretch. Just when the mobile is initialized, one of the two possible directions has to be chosen.

In [Mar93] a model for estimating car and pedestrian crossing rates at the border of an area is developed. This model considers the mobility conditions near the border of an area. The car crossing rate for an arbitrary area A is given by

$$\lambda_{car} = \sum_{i=1}^{n} \sum_{j=1}^{l_{nb}(i)} \rho_{i,j} \qquad \text{(cars/h)} \tag{2.4}$$

where n is the number of streets crossing the border, $l_{nb}(i)$ the number of lanes in street i, i = 1, 2, ..., n, and $D_{i,j}$ the car crossing rate for lane j of street i. Using the same modeling approach it is possible to estimate the pedestrian crossing rate too. However, for implementation of this model is necessary to know a lot of input statistical parameters such $l_c(i,j)$, the average distance between two cars moving in lane j of street i, $v(i,j)$, the average car speed in lane j of street i, etc. (see Fig.2.3).

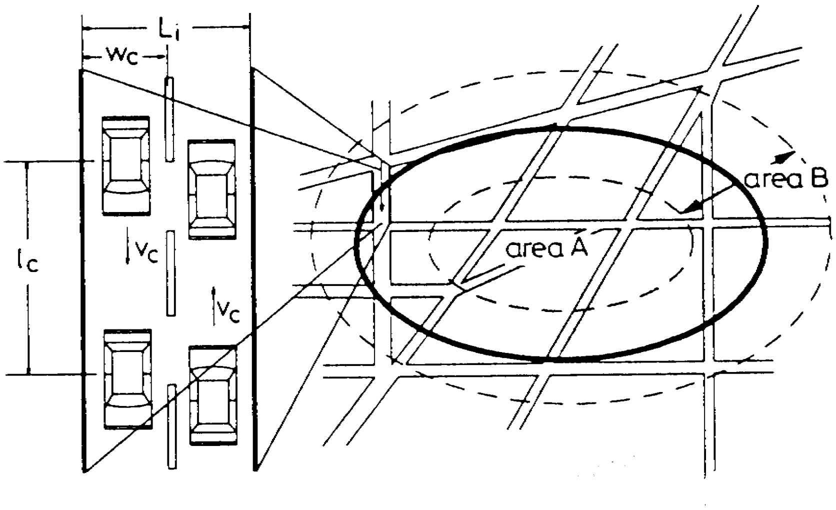


Figure 2.3 : Area model used for evaluating car crossing rate [Mar93].

In [Mar97] a street unit model is proposed. The mobile is allowed to move on a rectangular (Manhattan) grid only. The grid models the street pattern of suburban or urban areas. Parameters are the distances d_X and d_Y between crossroads in X- and Y-direction respectively. The speed is chosen from a normal distribution and can be updated periodically or area dependent as well as in the previous models. Direction changes can occur at every crossroad, where the probabilities can be different for each of the four possible directions and every crossroad. The Manhattan description is useful to represent many square grided cities. However, it is also has the flexibility to approximate any kind of path as a superimposed high way or ring roads whose line out depart from the Manhattan outline. Using dummy streets, irregular paths can be denoted to the desired approximation degree but the computation effort and complexity increase rapidly with them.

2.2.4.2 Tracing of the Random Movement

One of the earliest and comprehensive two-dimensional mobility models is the one developed by Guerin [Gue87]. Two approaches are used. The first one relies on a computer simulation allowing a general model for mobiles behavior, where changes in direction are allowed at exponentially distributed time intervals. An example is provided in Fig. 2.4 where a mobile goes through two handovers and two changes of direction before call termination. (The considering cellular system are formed only of “circular“ cells. This assumption and the reflection principle allow to bring the handover call back into the initial cell, reducing the entire system to the small bounded area of single cell.) All mobiles are assumed to keep the same constant speed for the entire duration of a call. The choice of an exponential distribution for the time between changes of direction was based on the fact that the time of the last change of direction may hardly provide any information on the time to the next change of direction.

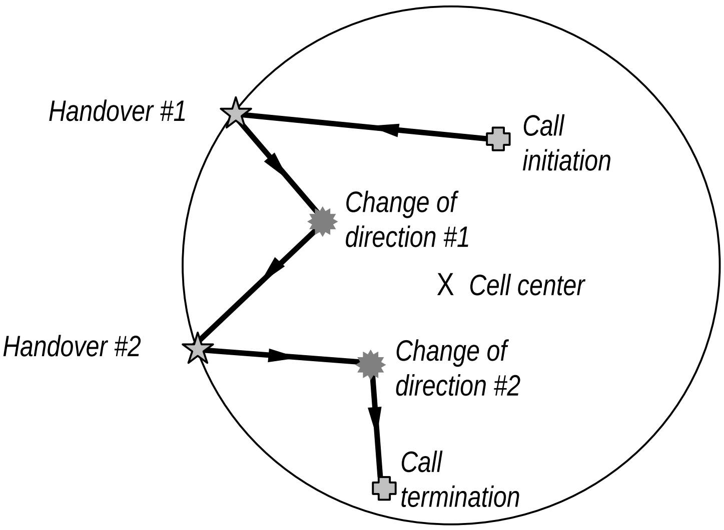


Figure 2.4 : Vehicle motion: path of a mobile going through two handoffs and two changes of direction before cell termination [Gue87].

The second approach is analytical, and assume a simplified system where mobiles keep constant directions. In the analysis, four orthogonal directions are considered, and no direction change is allowed so that the average number of handovers per call is expressed as a weighted sum of linear terms in the ratio of cell radius to average mobile speed. The waiting coefficients are derived based on the specific geometry of cell packing. The probability that a call goes through at least N handovers is given by

$$\Pr[handovers \geq N] = \int_0^{\infty} \Pr[T_N \leq t]\, pdf_c(t)\, dt \tag{2.5}$$

where $\Pr[T_N \leq t]$ is the probability that the N-*th* cell boundary crossing will take place before time t, and $pdf_c(t)$ is the call duration probability density function. With R denoting cell radius, $\bar{v}$, average mobile speed, and μ the inverse average call duration,

$$\alpha = \frac{R\mu}{\bar{v}} \tag{2.6}$$

is defined as a key parameter aiming to allow for comparisons between different cellular systems and the probability of N handovers is derived as a function of ″.

Guerin's derivation of channel occupancy time distribution, however, does not take into account any effects that call blocking and call dropping may have. The conclusion is that the exponential assumption is still valid for channel holding time distribution in cellular systems with the mean channel holding time, t_{HOLD}, given by

$$t_{HOLD} = \frac{\alpha}{\mu(\mu + 3 + 2\sqrt{3})} \;. \tag{2.7}$$

This result is not tested against decreasing cell sizes.

Zonoozi and Dassanayake [Zon95], [Zon97] offer a mathematical formulation for the systematic tracking of the random movement of a mobile station in a cellular environment. It incorporates mobility parameters under generalized conditions in a quasirandom fashion with assigned degrees of freedom, so that the model could be tailored to be applicable in most cellular systems.

This mobility model is used to characterize different mobility-related traffic parameters in cellular systems. These include the distribution of the cell residence time of both new and handover calls, channel holding time, and the average number of handovers. It is shown that the cell sojourn time can be described by the generalized gamma distribution (Appendix A) of the form:

$$pdf(t;a,b,c)=\frac{c}{b^{ac}\Gamma(a)}t^{ac-1}e^{-(\frac{t}{b})^c}, \qquad t,a,b,c>0 \tag{2.8}$$

where $\Gamma(a)$ is the gamma function, defined as

$$\Gamma(a)=\int_0^{\infty}x^{a-1}e^{-x}dx, \qquad a>0,\ a\in R. \tag{2.9}$$

The evaluation of the agreement between the distributions obtained by simulation and the best-fit generalized gamma distribution is done by using the Chi-Square goodness-of-fit test, (Appendix B).

These studies, however, either impose limitations on the degrees of freedom in the direction of motion or assume some of the important parameters, like the velocities of mobiles, probability of turning, etc. as coincidental but without any explication, derivation or proof.

Analytical models using rectangular or hexagonal radio cell bases do not take the actual road system into account, whilst models which are accurately based on the actual traffic system of a certain area require the collection and processing of extensive data [Ses92].

Application of the random movement tracing mobility models to a real geographical area is not straightforward. As such, a uniform spatial and temporal distribution of users underlying the call and mobility model is typically assumed for validation of resource allocation and location management protocols. This can lead to misleading conclusions about real networks [Lam97].

Next subsections present a comprehensive approach to mobility and teletraffic modeling for real networks. A primary contribution is the use of transportation studies results to model subscriber distribution and behavior for a real service area.

2.3 Mobility Modeling

The proposed mobility model [Bra97a], [Bra98] will describe the actual movement of subscriber units in vehicular traffic. The road network pattern, street length between crossroads, street width, traffic regulations and subscriber behaviour are included. The considered mobility model distinguishes pedestrians and vehicles to better characterise their movements in the system. The necessity to distinct users with different mobility behaviour was shown in Chapter 2.1.1. The presented approach does not distinguish the user flows in the streets of the service area but models the user mobility in dependence of the different traffic paths of each mobile in the system. In this chapter, the mobility model is introduced for one class of users, e.g. car drivers. It is separately applied for all classes to determine the transition rates per user between the cells in the system. These transition rates are the mobility values required for the teletraffic analysis (see Chapters 3 and 4).

Figure 2.5 presents an arbitrary vehicle route in a typical European city, i.e. Vienna. Vienna has grown over the centuries, when motor vehicle were unknown, and today houses a population of 1.5 million. It illustrates that the mobile deviation from its current direction rarely exceeds 90°. The subscriber unit seems to follow more or less one certain direction. Though the heterogeneous street pattern of an urban setting provides subscribers with a lot of choices, they mostly use major roads. Urban traffic planners encourage this by a number of traffic regulations.

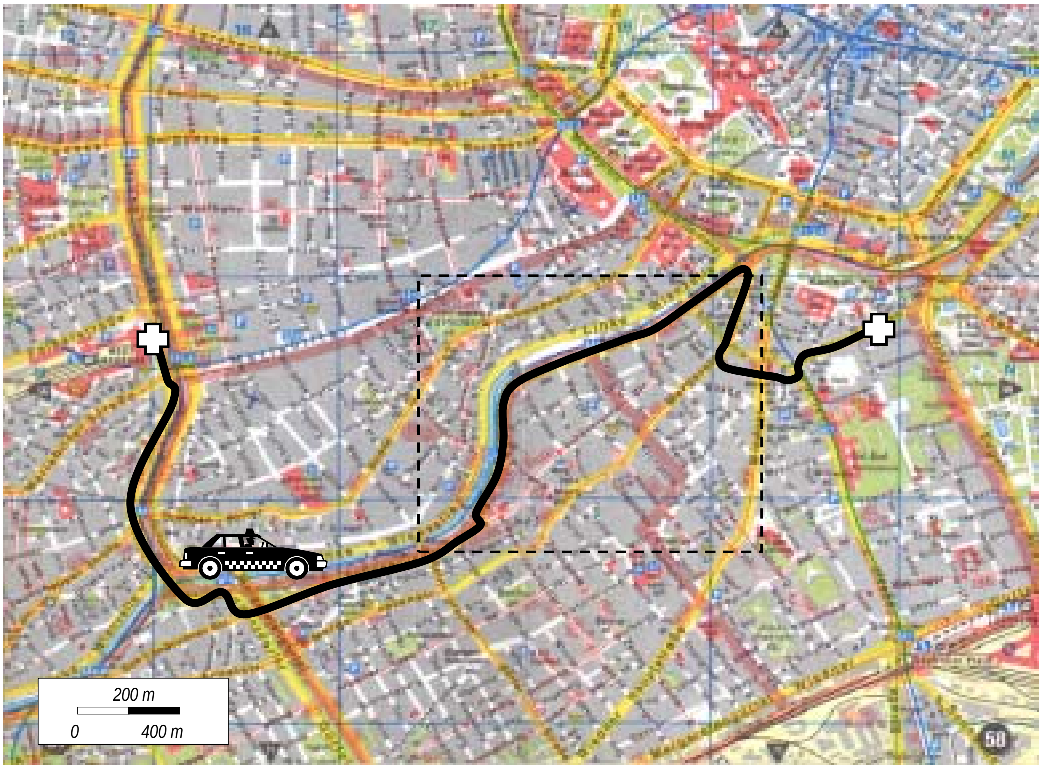


Figure 2.5 : A vehicle route in a typical European city (Vienna).

The determination of the time spent by a subscriber unit in the coverage area of a cell (cell sojourn time) is, with respect to service quality evaluation and the improvement thereof, of major importance. It is current practice to classify the cells according to the arrival of the call. In call-initiated cells the call is newly placed within the cell. Handover-call cells refer to a current cell to which calls have been handed over from neighbouring cells.

2.3.1 Starting Position

A mobile call can be initiated or received at any point within the cell along the path of the vehicle (Fig. 2.6). The call initiating position decides whether the calculated results show the remaining or the handover sojourn time, t_{rs} or t_{hs} . The travelling subscriber unit will exit the call-initiated cell after having used up the remaining sojourn time t_{rs} . The graph shows an arbitrary traffic path which includes all crossroads a subscriber unit would pass. The vectors $\vec{d}_i$ represent both the street-length value between crossroads, $|\vec{d}_i|$, and the direction of movement. The average velocities v_i are related to the different sections of the traffic path.

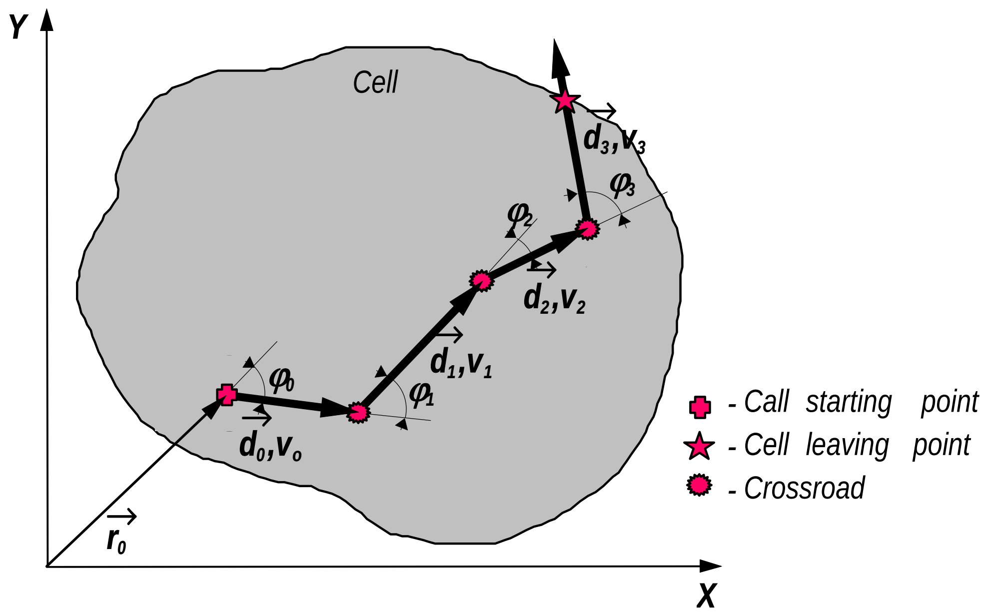


Figure 2.6 **:** Tracing a mobile within the cell. Remaining sojourn time in the call-initiated cell.

The uniform distribution used for the spatial location of call initiations was chosen for two reasons. It seems to give a fair representation of reality for cellular systems with homogeneous population density, and furthermore it is consistent with the initial assumption of traffic-equivalent cells throughout the system. This distribution can, however, be ***easily*** modified to fit a particular system (e.g., city centre with shopping malls or high density traffic roads).

Throughout a cellular system the relative orientation of streets and cells might vary somewhat randomly, giving on the average an approximately uniform distribution of cell border crossing locations. Figure 2.7 shows that handover-call cells have their starting point somewhere on cell boundaries.

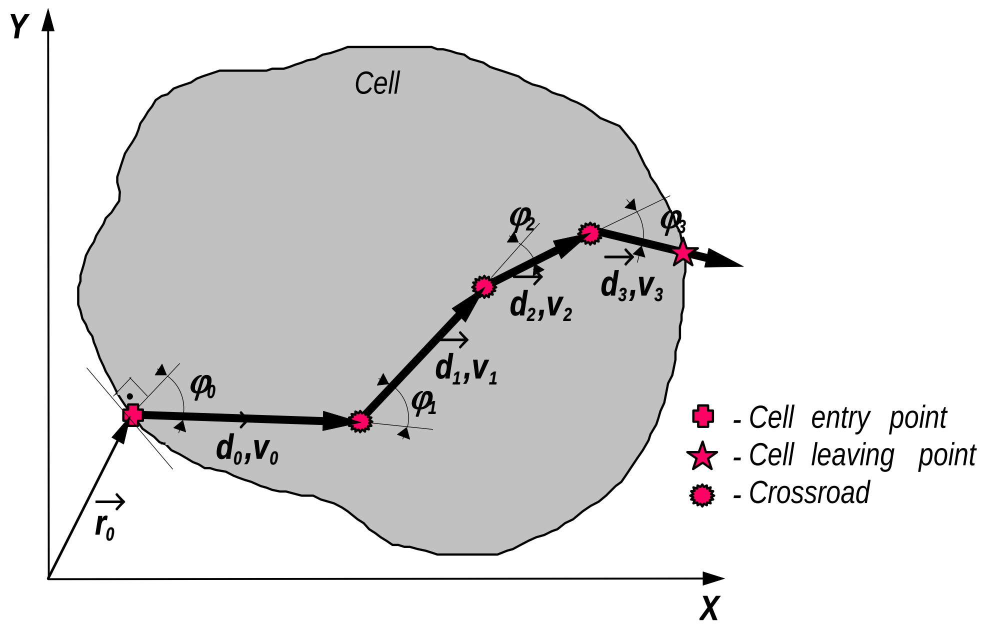


Figure 2.7 : Tracing a mobile within the cell. Handover remaining sojourn time in the handover-call cell.

Figure 2.6 and Fig. 2.7 show the trajectory of a mobile subscriber in the cellular environment. If $\vec{r}_0\,(x_0,\ y_0)$ denotes the initial position, the following relations provide the successive locations of the mobile user moving in random directions:

$$\begin{aligned} &\vec{r}_1(x_1,\ y_1) = \vec{r}_0 + \vec{d}_0(d_0, \varphi_0), \\ &\vec{r}_2(x_2,\ y_2) = \vec{r}_1 + \vec{d}_1(d_1, \varphi_1), \\ &\quad \cdot \quad \cdot \quad \cdot \quad , \end{aligned} \tag{2.10}$$

where φ_i is the change in direction with respect to the previously direction at last crossroad. In order to simplify the formulation and to enable the consideration of cells with arbitrary shapes, we define a Cartesian coordinate system (X, Y).

2.3.2 Probability of a User Selecting a Specific Direction Upon Reaching a Crossroad

Since the moving direction of a mobile is uniformly distributed between [$-\pi$, π), the probability density of the start angle φ_0 is given by:

$$pdf(\varphi_0) = \begin{cases} \dfrac{1}{2\pi} & for \quad -\pi \le \varphi_0 < \pi \\ 0 & otherwise \end{cases} . \tag{2.11}$$

The probability density function of direction for a boundary crossing mobile has a direction bias toward the normal [Xie93] as shown in the Fig. 2.7 (in this case φ_0 is the angle between the normal of the cell boundary and the moving direction of the mobile) and is given by:

$$pdf(\varphi_0) = \begin{cases} \dfrac{1}{2\pi}\cos\varphi_0 & for \quad -\dfrac{\pi}{2} \le \varphi_0 < \dfrac{\pi}{2} \\ 0 & otherwise \end{cases}. \tag{2.12}$$

The relative direction changes at each crossroad, φ_i, depends on the street network pattern and the traffic situation. The angle φ_i can be expressed by the realisation of one of four random variables. Each random variable is normally distributed, with means estimated 90° apart. The probabilities when assigning one of these variables to φ_i depend on traffic regulations on the one hand (e.g., traffic users are more likely to turn right than left) and the Highway Code (e.g., one-way traffic in densely populated areas is only allowed to turn right/left at every second crossroad). Therefore, the probability density function of φ_i is given as follows:

$$pdf(\varphi_i) = \frac{1}{1 + w_{90^\circ} + w_{-90^\circ} + w_{180^\circ}} \cdot \frac{1}{\sigma_\varphi\sqrt{2\pi}} \left(e^{-\frac{\varphi_i^2}{2\sigma_\varphi^2}} + w_{90^\circ} e^{-\frac{\left(\varphi_i - \frac{\pi}{2}\right)^2}{2\sigma_\varphi^2}} + w_{-90^\circ} e^{-\frac{\left(\varphi_i + \frac{\pi}{2}\right)^2}{2\sigma_\varphi^2}} + w_{180^\circ} e^{-\frac{(\varphi_i - \pi)^2}{2\sigma_\varphi^2}} \right) \tag{2.13}$$

where:

w_{90°, w_{-90°, w_{180° - weight factors corresponding to probabilities,

σ_φ - standard deviation of direction distributions, assumed to be equal for all four distributions.

The value of σ_φ depends on the road network pattern. A discrete and irregular road network pattern shows a higher value (Fig. 2.8) than a Manhattan grid where the streets are perpendicular to each other.

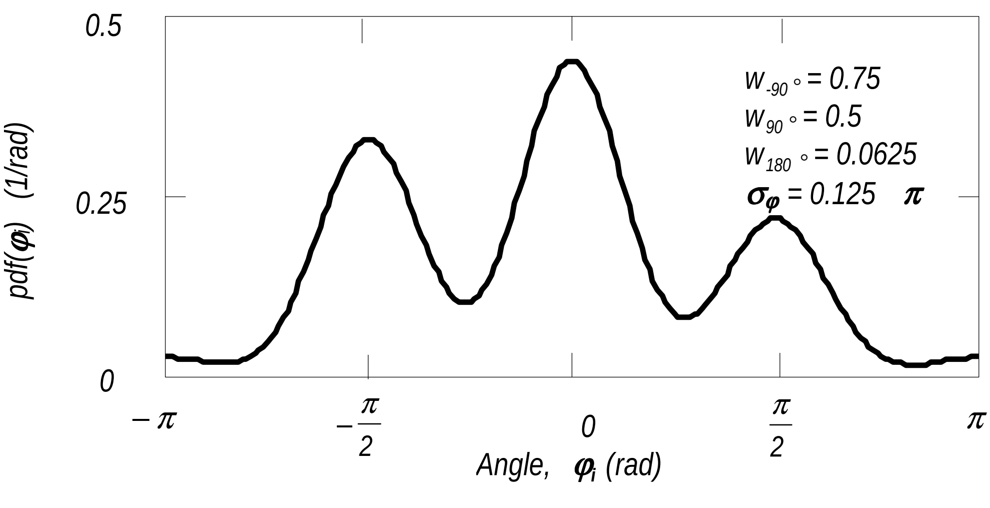


Figure 2.8 : The probability density function of direction changes after each crossroad.

The polar plot of $pdf(\varphi_i)$ (Fig. 2.9) represents a distribution diagram of relative direction changes. Figure 2.9 also illustrates the impact of the different weight factors $w_{90°}$, $w_{-90°}$, $w_{180°}$ and of the deviation σ_φ.

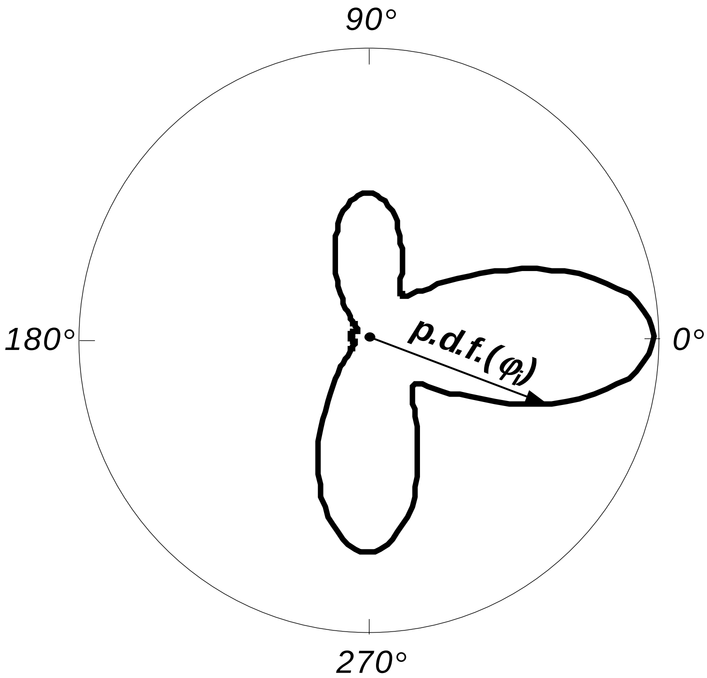


Figure 2.9 **:** The polar plot of $pdf(\varphi_i)$.

2.3.3 Time Required to Cross Two Crossroads

The distance traveled (or time spend) by a mobile user in a cell depends on its direction, point of entry, cell shape and changes of direction. What is of interest, however, is not the actual mobile trajectories but the distribution of traversal lengths (traversal times). With this in mind we propose to derive, first, the street length statistic, second, the speed statistic and then to calculate the time spend by mobile user traveling between two crossroads. Depending on the city structure, a mobile can move in different paths with different speeds. The effects of change in direction and speed must be considered together.

2.3.3.1 Street Length Statistic

The street lengths between crossroads, d_i, in European cities may also be presented as a random variable. The projections of two arbitrary streets have been plotted in the domain of the X- and Y-axis, respectively (Fig. 2.10).

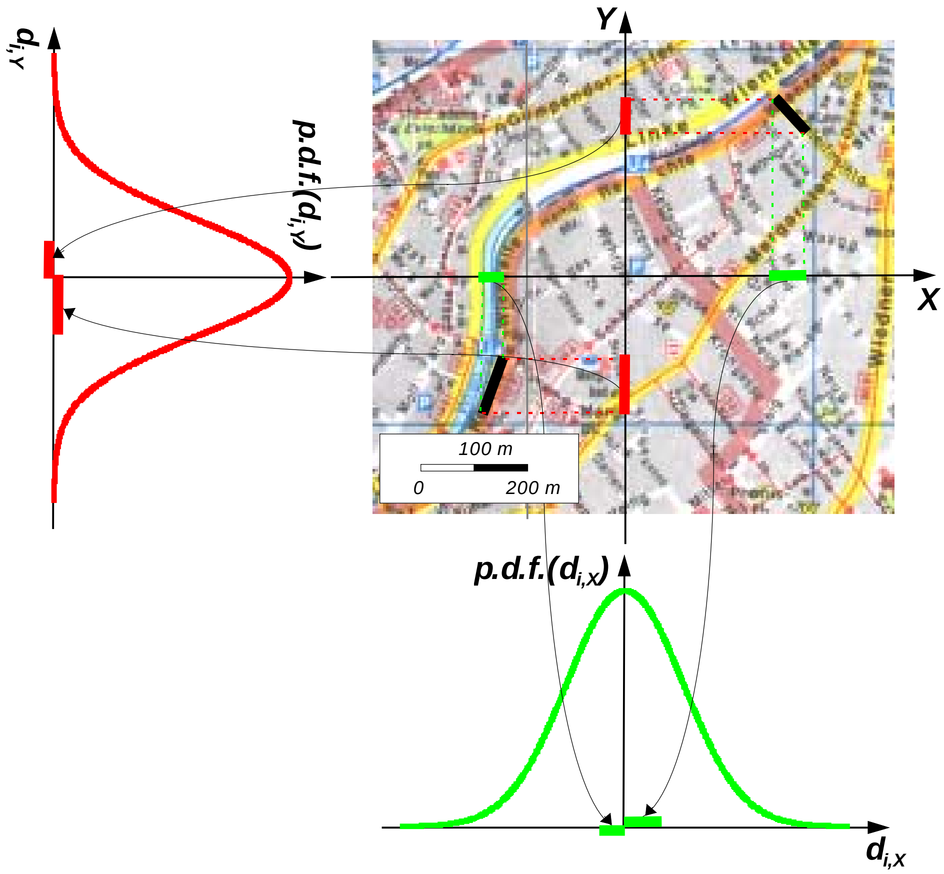


***Figure 2.10* :** Derivation of the probability density function of street length.

Since the streets take a random course with respect of the axes of a Cartesian coordinate system, their projections $d_{i,X}$ and $d_{i,Y}$ shall be regarded as normally distributed random variables. In areas with an irregular street network pattern the random variables $d_{i,X}$ and $d_{i,Y}$ can be characterized as statistically independent and normally distributed, with zero mean and showing the same variance. Therefore, the street length between crossroads:

$$d_i = \sqrt{d_{i,X}^2 + d_{i,Y}^2} \tag{2.14}$$

turns out to be a Rayleigh-distribution (Fig. 2.11):

$$pdf(d_i) = \begin{cases} \dfrac{d_i}{\sigma_d^2} e^{-\frac{d_i^2}{2\sigma_d^2}} & for \quad d_i > 0 \\ 0 & for \quad d_i \leq 0 \end{cases} \qquad where \quad \sigma_d = \bar{d}\sqrt{\frac{2}{\pi}} \; . \tag{2.15}$$

The mean street length $\bar{d}$ may differ somewhat within the different parts of the city. Calculations for Vienna, Austria, show that $\bar{d}$ =80-110m in the city center whereas it amounts to $\bar{d}$ =110-170m in the outskirts.

Though the heterogeneous street pattern of an urban setting provides subscribers with a lot of choices where to drive, they mostly use major roads. Urban traffic planners encourage this by a number of traffic regulations. When the majority of terminals travel on major roads only, the probability density of d_i can be approximated by a Rice-distribution:

$$pdf(d_i) = \begin{cases} \dfrac{d_i}{\sigma_d^2} e^{-\frac{d_i^2+\bar{d}^2}{2\sigma_d^2}} I_0\left(\dfrac{d_i \bar{d}}{\sigma_d^2}\right) & \text{for} \quad d_i > 0 \\ 0 & \text{for} \quad d_i \le 0 \end{cases} \quad \text{where} \quad 0.75\,\bar{d}\sqrt{\frac{2}{\pi}} < \sigma_d < 1.5\,\bar{d}\sqrt{\frac{2}{\pi}} \,. \tag{2.16}$$

Here $\bar{d}$ is taken as the average length of major roads between crossroads.

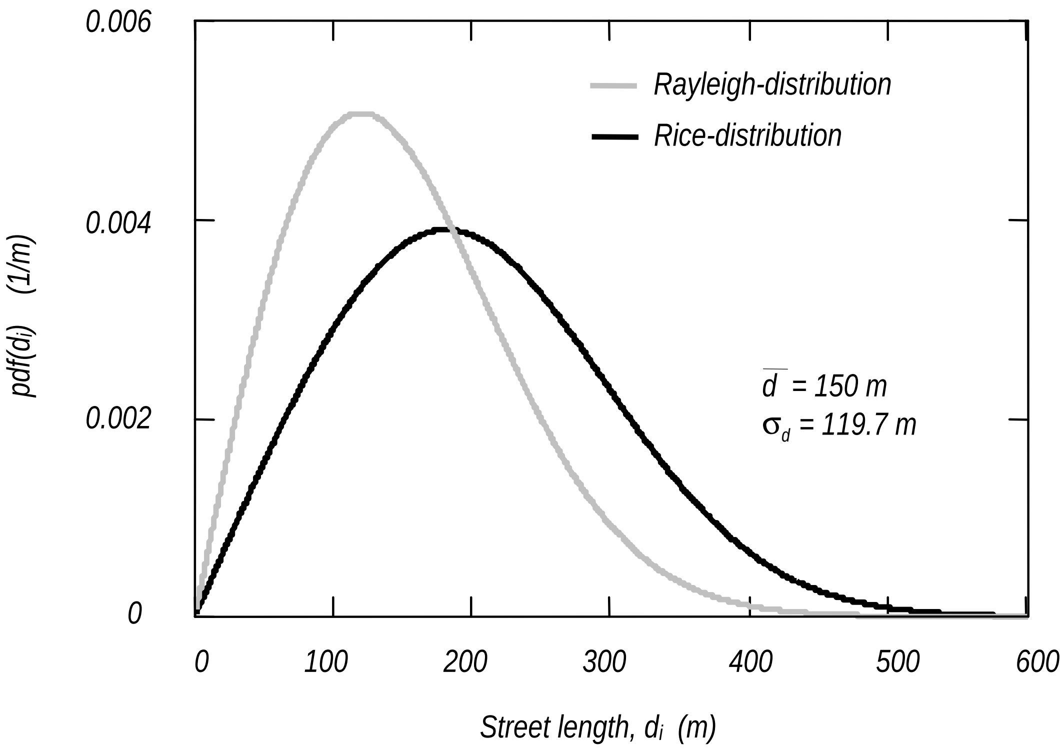


Figure 2.11 **:** The probability density function of street length.

2.3.3.2 Average Car and Pedestrian Speed Statistic

Instantaneous mobile speed varies continuously but, like the exact trajectory of a mobile, is of little interest for our model. The model avoids becoming excessively involved by assuming that the velocity of the subscriber unit does not change while covering the distance d_i which allows an equation with the ***average*** velocity v_i. All of these average velocities can be expressed as vectors whose orientations correspond to the street directions. In analogy with the calculation of street-length statistic it can also be assumed that the average velocity is Rayleigh/Rice distributed. As we have mentioned before, traffic is bundled on major roads where the average speed might be higher than in the urban streets. Measurements in Helsinki [Zee94] and Vienna (see for more details Chapter 2.4) suggest to add a second term to the speed distribution to account for this. Empirical transportation engineering studies show in case of free street flow (*Brownian Motion*) that at a given point, the mobile speed is normally distributed with the street speed limit as the mean and some standard deviation [May90], [Rob94]. So to enable a more accurate description of the actual velocity distribution, we add such a term and assume that the velocity of subscribers on major roads is normally distributed, and get (Fig. 2.12):

$$pdf(v_i) = \begin{cases} \dfrac{1}{1+w_{mr}}\left[\dfrac{v_i}{\sigma_v^{\,2}} e^{-\frac{v_i^2+\bar{v}^2}{2\sigma_v^2}} I_0\left(\dfrac{v_i\bar{v}}{\sigma_v^{\,2}}\right) + w_{mr}\dfrac{1}{\sigma_v\sqrt{2\pi}} e^{-\frac{(v_i-\overline{v_{mr}})^2}{2\sigma_v^2}}\right] & for \quad v_i > 0 \\ 0 & for \quad v_i \le 0 \end{cases} \tag{2.17}$$

where:

w_{mr} - weight factor for fraction of cars on major roads,
$\bar{v}, \bar{v}_{mr}$ - mean velocities of city and major-road traffic,
σ_v - deviation.

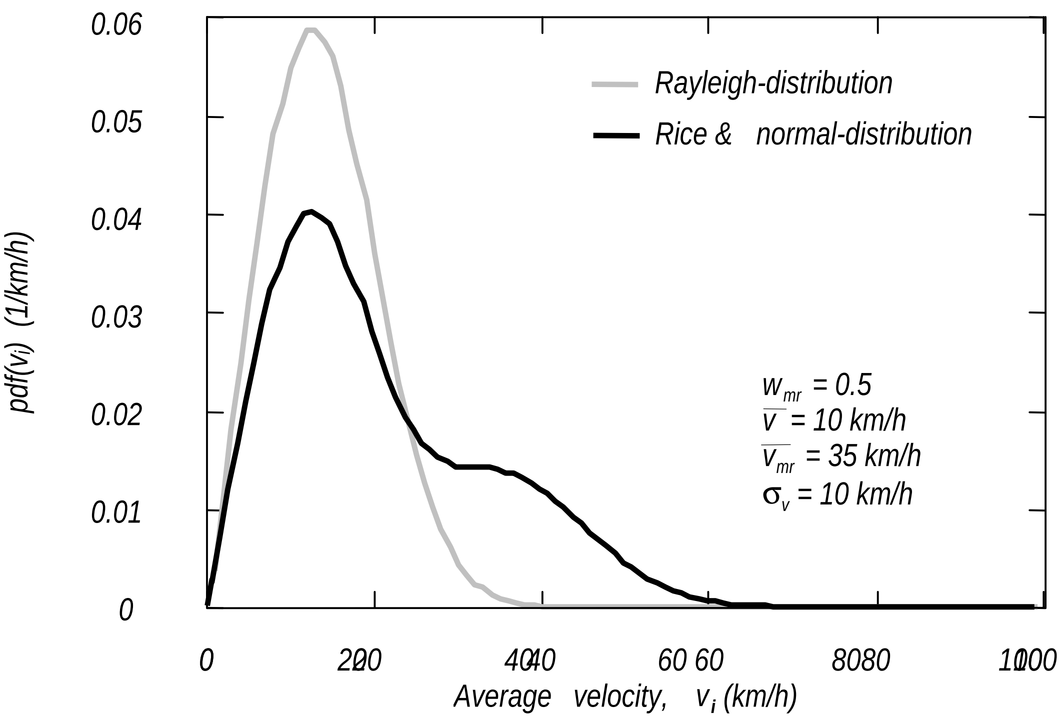


Figure 2.12 : The probability density function of average velocity for vehicles.

The analysis of the mobility parameters imposes the consideration of the mobility behavior of any passenger/pedestrian located at the street unit. Pedestrians move at slow speeds (2-5km/h), while their motion can be characterized as continuous (walking), Fig. 2.13. The behavior of pedestrian can mainly be guided by the following rules:

- Minimization of walking time,

- Quasi street bounded walk,
- Changes of walk direction are not possible only at crossroads. This leads to a reduction of effective street length.

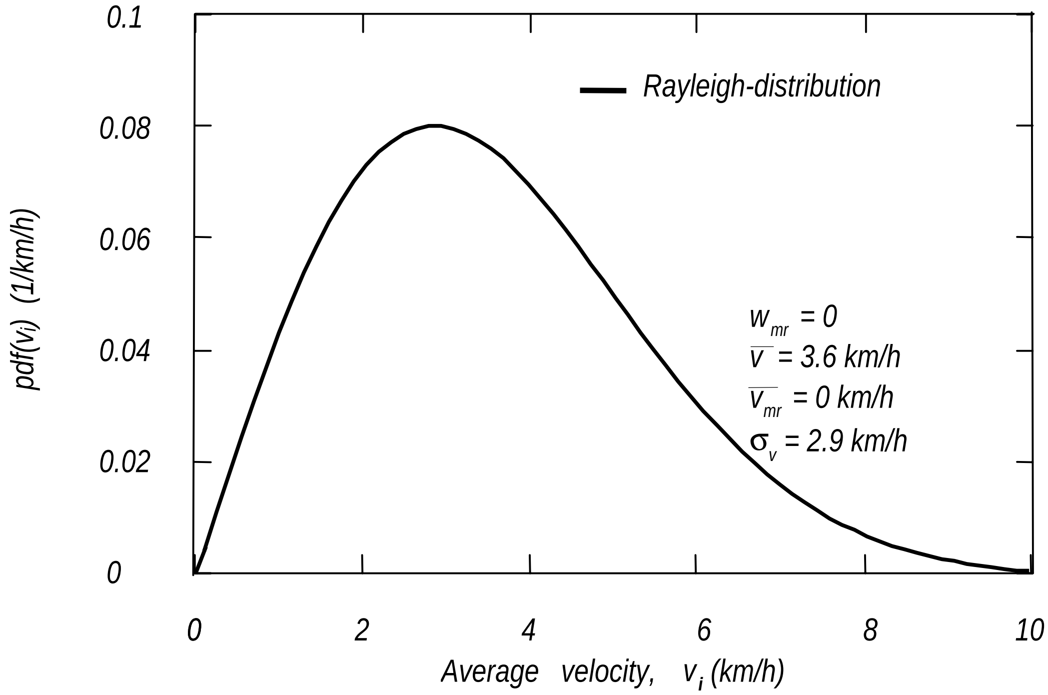


Figure 2.13 **:** The probability density function of average velocity for pedestrians.

The value of the individual street length between crossroads d_i, and the corresponding average velocities v_i being known, we are now in the position to calculate the remaining or the handover sojourn time, t_{rs} or t_{hs}. A computer simulation tool to obtain these statistical variables is described in Chapter 3.2.3.

2.4 Model Parameters Estimation and Measurement

The lack of statistical information or its non-adaptation for cellular network planning is an important problem in the modeling of user mobility in cellular networks. As mentioned, we deduce the different user flows from statistical data on the vehicular traffic in the studied area. These data are obtained from public authorities in charge of transportation systems. The presented study is made on the example of the city of Vienna (Austria). In Fig. 2.14, a density distribution graph of vehicular traffic over the whole city area is shown [MA18].

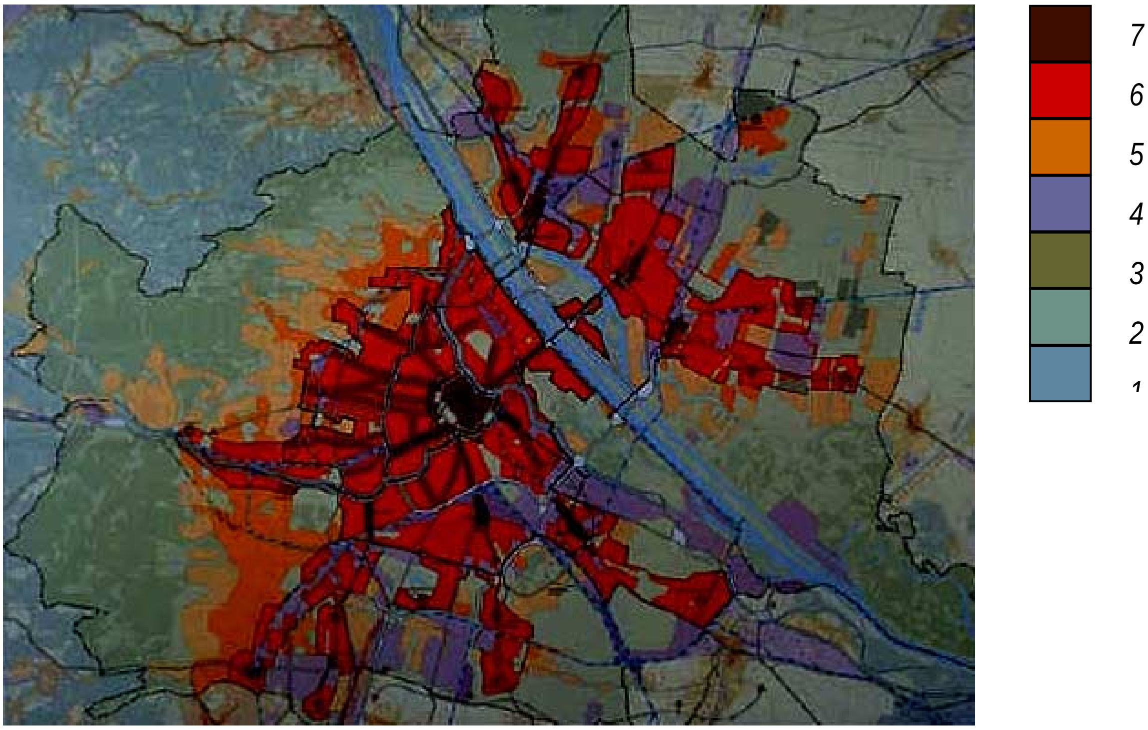


Figure 2.14 **:** Traffic density on the streets of Vienna (source: City Government of Vienna, Municipal authority 18: Town Development and Town Planning) [MA18].

The vehicular traffic map in the city distinguishes seven classes of streets. We deduce from these data the flows of vehicular users and their densities in the streets. The vehicle flows for the different street classes attributed to the road graph are shown in Tab. 2.1:

Table 2.1 **:** The vehicle flows/day for the different street classes.

Street class	Vehicles/day
1	<1500
2	1500-3000
3	3000-6000
4	6000-10,000
5	10,000-20,000
6	20,000-30,000
7	>40,000

The mobile network operators can, by means of different measurements, verify the dimensioning of the user flows in an existing system and extrapolate and adjust the input parameters for the studies on new systems or for the case of modification in existing networks.

For example, in *GSM* systems [GSM12], the operator can measure the number of arriving and leaving inter-cellular handovers in each cell and thus estimates the street bounded user flow at border between cells.

The measurements of the pedestrian traffic in the cities are rare in the sense that in most cases only vehicular traffic is subject to measurements. Extensive measurements in the city center of Helsinki [Zee94] provide the opportunity to obtain a realistic traffic characterization of pedestrians. Helsinki cannot be considered as worst case scenario compared to central London or Paris, but it may provide valuable data about the traffic parameters in a common situation. The following measurements in the city center of Helsinki are reported:

- Flow of pedestrians for each link of the pedestrian network (average number of pedestrians passing by in each direction between 6 a.m. and 8 p.m. on a normal working day).
- Flow of cars for each link of the car network (average number of cars passing by in each direction during the morning rush on a normal working day).

From traffic measurements it is known that the peak intensities of car and pedestrian traffic during a day do not necessarily coincide. In Fig. 2.15 an example of the distribution of the traffic intensity for pedestrians and cars during each hour of the day derived from a survey of the Dutch population in 1992 [CBS92] is depicted.

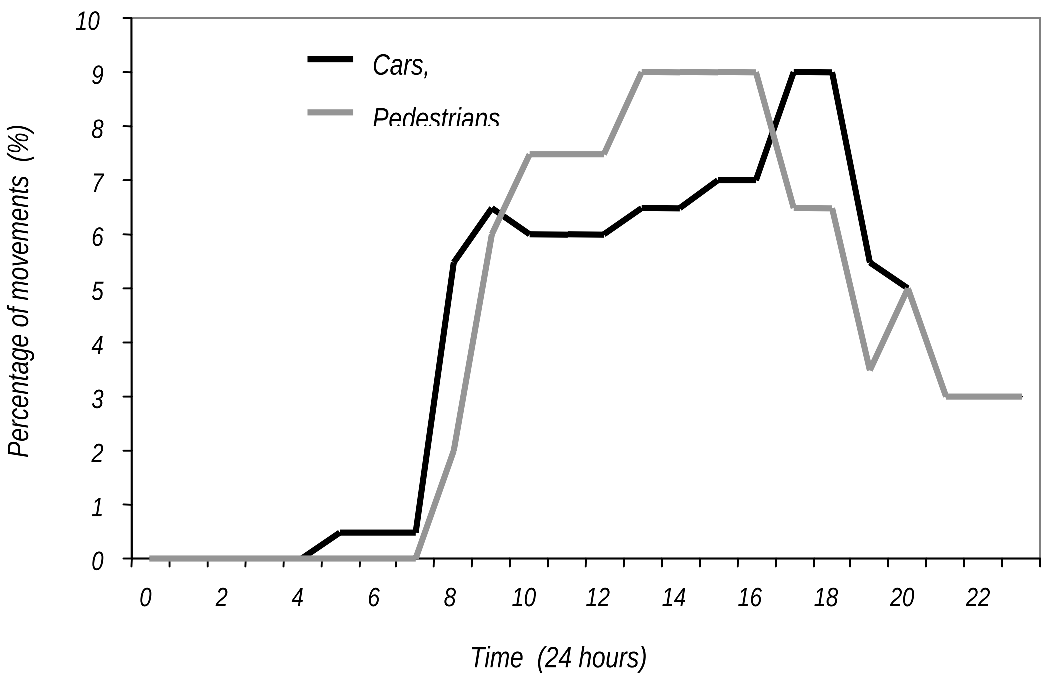


Figure 2.15 : Distribution of movements over a day [CBS92].

In the sequel, we assume that pedestrians and passengers mainly differ by their velocity. The pedestrian density distribution is supposed to be proportional to the vehicle density. If more precise information about the pedestrian flows is available, this assumption can be modified.

The traffic flow is a mobility parameter of prime interest to derive the amount of signaling of mobility procedures such as handover and location updating. Car passengers may more or less maintain their average sped but a pedestrian is likely to stand still or look for a private location to handle the call. From survey it is found that shopping is the major motive of pedestrian movements [CBS92]. Shops are so called attraction points of pedestrians. Therefore the density of shops could be used to predict the density of pedestrians within the area.

To verify the theoretical assumptions and to estimation of its parameters, we will take some of the rich measurement trials of the Mobilkom Austria AG, a Division of Telekom Austria AG. As the leading mobile communication network provider in Austria, Mobilkom AG is trying to support constantly a very high service quality to the clients by continuously quality control. For this reason a special equipped car for measurements is used all over the coverage plane in Austria (mainly stressed in the centers with high population density). The *Q-Voice* speech quality measurement system from Ascom Infrasys AG, Switzerland is used to initialize and perform a lot of calls. During each call, all the network related data are gathered and recorded (for instance, speech quality, received quality, handover processing, signaling issues etc.), where all these data are measured and stored over a very fine time reference. For each of these measurements is recorded, with the help of a integral *GPS* location receiver, the corresponding local situation of the trial car. Therefore the measured data in city area of Vienna allows us to compute a very fine statistic of the mean car velocity from a crossroad to the next crossroad. Figure 2.16 shows the measurement results for the velocity distribution in the city of Vienna (2nd District, Praterstern). The theoretical velocity model, that we investigate, is describing superbly the real velocity distribution. Through Chi-Square goodness-of-fit test (Appendix B) we could also determine the model parameters. The test has shown the following values of the parameters: w_{mr} =1.25, $\bar{v}$ = 10km/h, $\bar{v}_{mr}$ = 45km/h, σ_v = 10km/h.

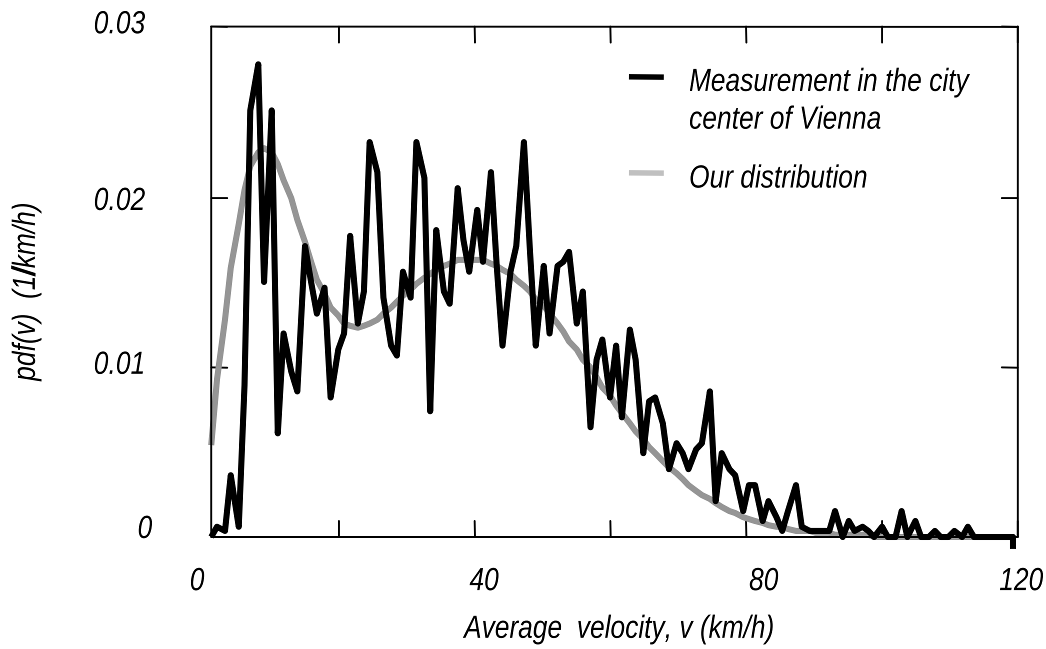


Figure 2.16 : The probability density function of average velocity for vehicles. Parameters estimation using real measurements data.

When the recorded measurement routes are overlaid over the city map of Vienna, then one can determine the probabilities of direction changes and from this one can derive the corresponding weight factors for direction changes statistics (cf. Eq. 2.13), Tab. 2.2.

***Table 2.2* :** The probabilities of direction changes for different street classes.

Street class	***Measured cross-road turnings***				***Corresponding weight factors***		
	No turn	*To right*	*To left*	*U-turn*	$W_{90°}$	$W_{-90°}$	$W_{180°}$
City center (3,4,5)	*253*	*401*	*327*	*19*	*1.585*	*1.292*	*0.075*
Outskirts (1,2,4,7)	*554*	*320*	*111*	*15*	*0.201*	*0.578*	*0.027*
Outskirts(1,3,4,5)	*410*	*309*	*255*	*26*	*0.622*	*0.754*	*0.063*

Further, with the help of the city map one can also determine the value for the standard deviation of direction distributions, σ_φ, for different street classes. At first will be measured the cross-road angles of the street pattern (Fig. 2.17) for all considered streets in a particular district.

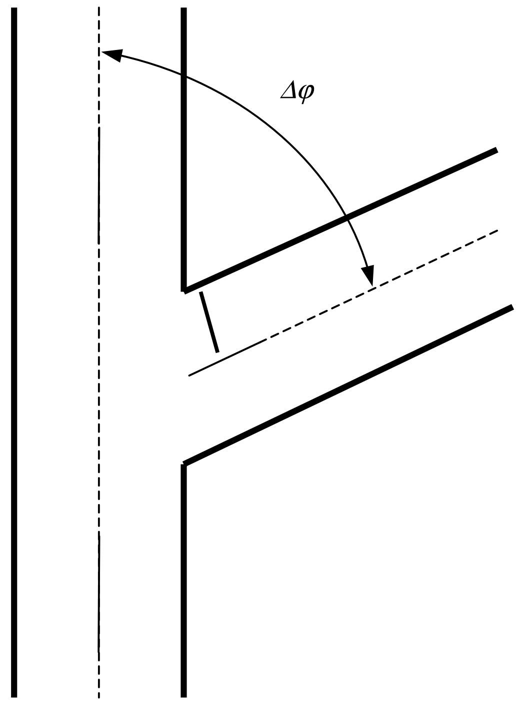


***Figure 2.17* :** Cross-road angle of the street pattern.

Then the results will be statistically analyzed (Fig. 2.18) and finally will be determined the values for the standard deviation, σ_φ, (Tab. 2.3).

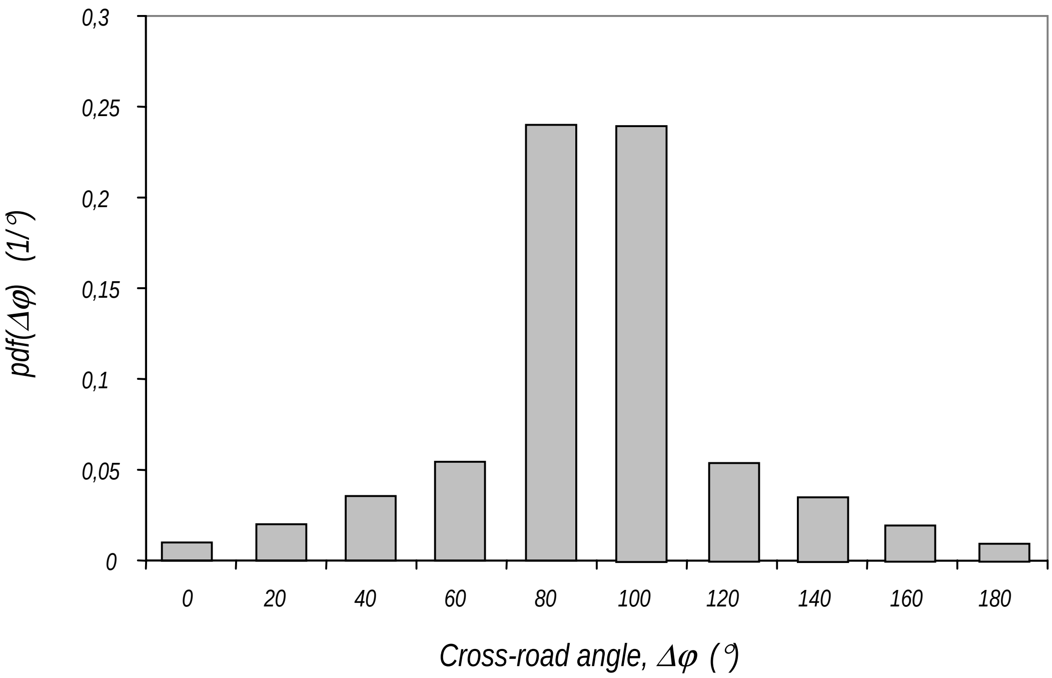


Figure 2.18 **:** The probability density function of cross-road angle.

Table 2.3 **:** The standard deviation of direction distributions, σ_φ, for different street classes.

Street class	Measured standard deviation, σ_φ (rad)
City center (3,4,5)	0.54
Outskirts (1,2,4,7)	0.27
Outskirts (1,3,4,5)	0.17

2.5 Model Validation

From the proposed mobility model the possible range of the density of pedestrians and cars on the street can be derived. The velocity probability density function corresponds with the actual subscriber movements and therefore enables a precise calculation of the average, as well as maximum, traffic flow. Figure 2.19 compares the results of our approach with the actual data collected in a test area with 675 cars per km-street.

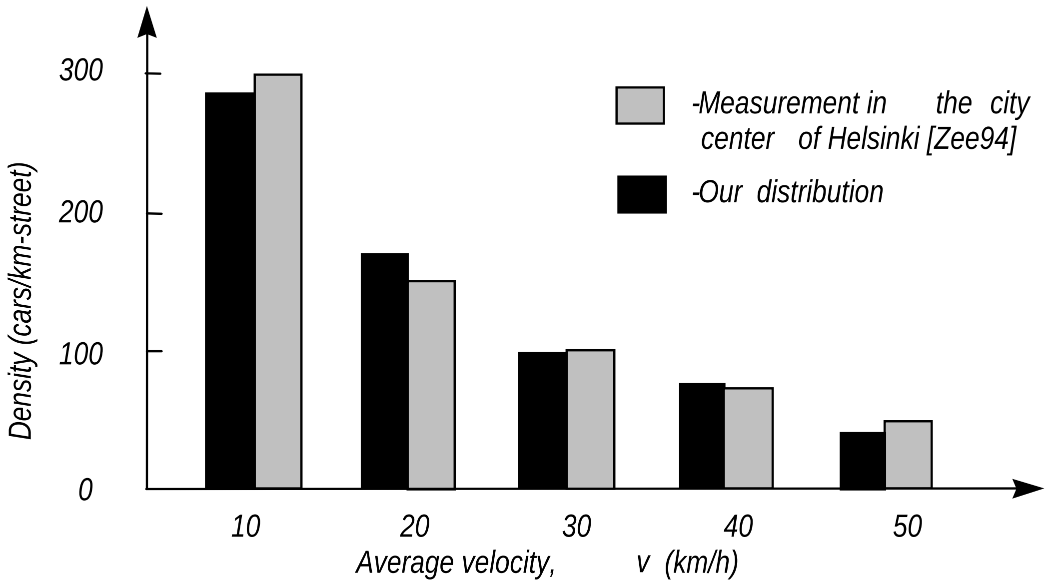


Figure 2.19 **:** Car density on streets (for maximum vehicular traffic flow).

Figure 2.20 compares the results of our approach with the actual data collected in a test area with 16,000 pedestrians per hour.

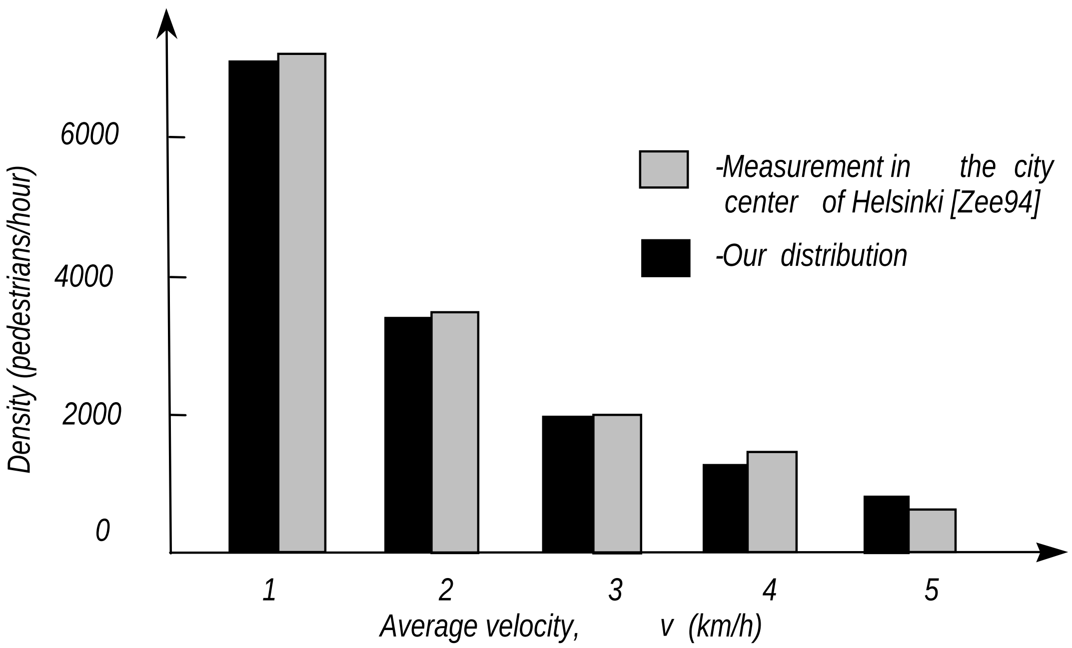


Figure 2.20 **:** Pedestrian density on streets (for maximum pedestrian traffic flow).

The proposed mobility model may be applied as a wide powerful aid in cellular networks design and optimization. Consequently the basic verification are to be related to these topics. The most important signaling and teletraffic related parameters such as sojourn time, handover rate, channel holding time, etc. will be determinate with respect to this models in the next chapter. They will be compared with the known theoretical or empirical relations and measurement data. Only through this means will be possible to reach a validated assertion about how good and accurate is the description of the actual subscribers behavior made by the proposed mobility model. Thus the mobility model must be integrated with a call model to describe the real subscriber behavior and its influence over the whole mobile communication system.

***The third**, to conduct my thoughts in such order that, by commencing with objects the simplest and easiest to know, I might ascend by little and little, and, as it were, step by step, to the knowledge of the more complex; assigning in thought a certain order even to those objects which in their own nature do not stand in a relation of antecedence and sequence.*

René Descartes
(DISCOURS DE LA MÉTHODE POUR BIEN CONDUIRE SA RAISON, ET CHERCHER LA VÉRITÉ DANS LES SCIENCES, 1637 - Discourse on the Method for Rightly Conducting One's Reason and Searching for Truth in the Sciences)

Chapter 3

Signaling and Teletraffic Related Parameters

3.1 Introduction

Aside from the radio subsystem, the network infrastructure architecture also plays an important role in determining the overall system performance. Furthermore, the specific environment of personal communications with multitiered cell architecture, enhanced handovers, and mobility control as well as use of dynamic resource assignment will result in substantial control traffic and will add another dimension to traffic management. Performance characteristics of the system and perceived quality of service *QoS* in modern wireless networks will be even more essential.

3.1.1 Performance Characteristics of the System

The performance of wireless networks, when circuit switching is used as the primary method of allocating the access channels, can be described by tailoring those measures used in traditional fixed networks to particular features of mobile cellular and personal communications. For background in performance measurement and modeling in the context of mobile cellular networks can be referred to [Rap93], [Jak94]. More specifically, three performance measures - the probability of call blocking, Pr_b , the probability of handover failure or handover-blocking, Pr_{hf} , and the probability of forced termination or call dropout during a call, Pr_d , - can be defined under the assumption of a continuous service area where the effect of call dropout due to insufficient received signal strength from the base station is negligible; otherwise, we need to introduce the fraction of useful service area.

It is worth noting that the mobile users not receiving radio coverage but wanting to make calls are "blocked" just as effectively as though all the channels were tied up. An "effective" system blocking probability can thus be defined that takes into account the channel blocking, $\Pr_b$, and radio coverage blocking, $\Pr_c$:

$$\Pr_s = 1 - \Pr_c(1 - \Pr_b) \ . \tag{3.1}$$

If $\Pr_s$ is specified as a system requirement, a trade-off between $\Pr_b$ and $\Pr_c$ is thus established.

Furthermore, in systems with traffic overflow capability, one may consider the probability of call loss $\Pr_l$ in addition to the probability of blocking of calls offered to a cell. Carried traffic, including or excluding the calls admitted by the system but not successfully completed, is a particularly important measure of system performance and can be determined for a given offered load. To take into account the effectiveness of the mobile management architecture more meaningfully, one may also define probability of call delivery as another important network performance when the called subscriber is available. Other performance measures include call setup delay, time to be recognized as a valid subscriber in a network, and the time during which a call stays in a handover region. Figure 3.1 presents a simple, rather general model of the cell and associated traffic, where λ_i denotes the new-call arrival rate, and λ_h the handover-call arrival rate. Understanding the mobility aspect of the users is essential in the evaluation of the network design and performance parameters.

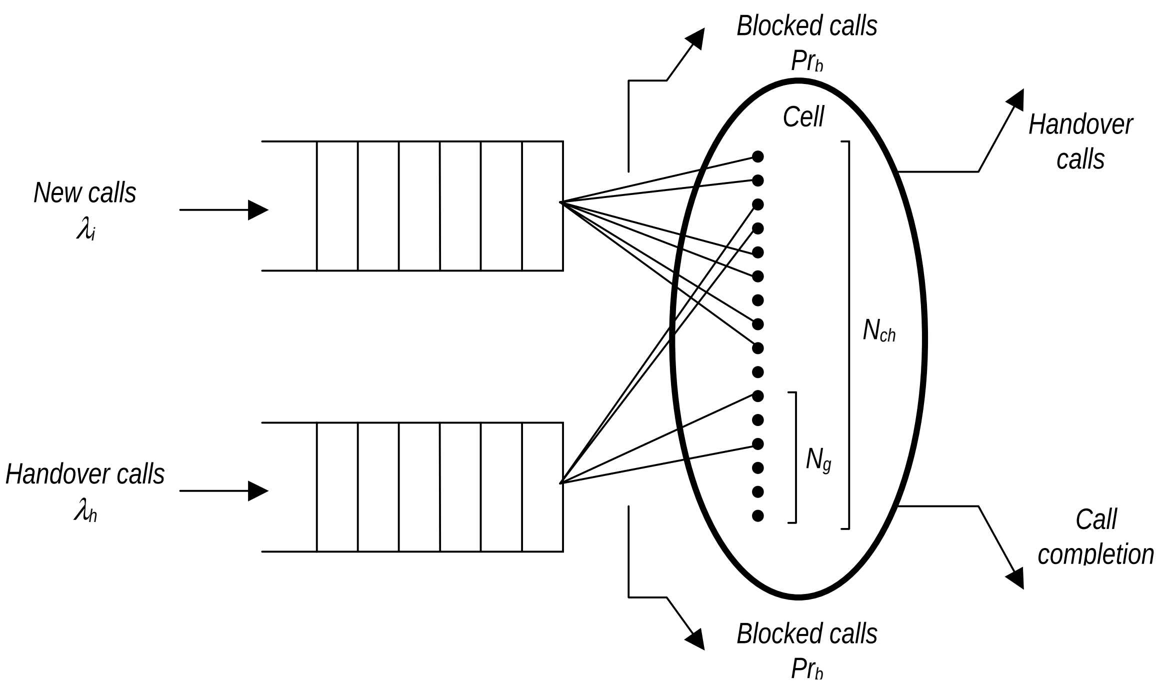


Figure 3.1 : New and handover traffic processes, total number of channels N_{ch}, and guard channels N_g in a cell.

The important parameters directly related to mobility include channel occupancy time and the probability of cell boundary crossing. Note that these parameters are important not only because they influence actual traffic load behavior but also because they relate to the control traffic and therefore her useful system capacity.

Note that total offered traffic to a cell is dependent on the handover traffic, which in turn depends on the total offered traffic to the cell. Using flow equilibrium property, we can write

$$\lambda_h = \Pr_h[(1-\Pr_b)\lambda_i + (1-\Pr_{hf})\lambda_h] \ . \tag{3.2}$$

And subsequently solve for λ_h as follows:

$$\lambda_h = \frac{\Pr_h(1-\Pr_b)}{[1-\Pr_h(1-\Pr_{hf})]}\lambda_i \ . \tag{3.3}$$

Once the geographic coverage and demand information is acquired, the system designer must determine how many channels $N = N_{ch} - N_g$ will need to be assigned to each cell in the system. The procedure used is relatively straightforward. First, a Quality of Service (*QoS*) for the system is chosen. Next the demand of traffic per cell, usually measured in Erlangs or traffic units (*TU*), is calculated for the peak busy hour. The number of channels can then be arrived at by using either the Poisson, Erlang B, or Erlang C formulas, Fig. 3.2. Once the system is built and operational, the traffic statistics are gathered and analyzed. Any modifications necessary to retain service quality at the desired level will become evident from traffic analysis.

As anticipated, traffic engineering for mobile cellular networks builds on the wealth of knowledge available for traffic engineering of fixed networks and, where, applicable will use engineering practices for those. However, the scarcity of spectrum and the dependence of radio channel quality on mobility characteristics, propagation conditions and traffic source activity add new dimensions to the traditional traffic considerations.

Two aspects unique to cellular systems are spectrum reuse and handover process. The former allows spectrum scarcity to be overcome; the latter combats channel quality degradation. Spectrum reuse and handover process are related in that the increase in the number of radio channels per unit area enabled by spectrum reuse is normally associated with an increase in the number of handover request. Since a failed handover request negatively affects user perception of service quality, and a connection cut off due to unsuccessful handover is very annoying since it relates to established connections, handover requests are normally handled with some form of priority over calls. Hence, a trade-off exists between spectrum reuse, call blocking, and handover failure. Assessing this trade-off is a more important task for traffic engineering of cellular mobile communications networks.

A typical function of mobile communications systems is to monitor the channel quality and try to allocate a new channel (handover function) when the one in use no longer meets minimum quality requirements. Allocating a new channel calls for almost immediate availability of radio resources and rises teletraffic problems which range from service prioritization to admission control. The channel quality is assessed by considering a range of metrics and depends on the service type. The "quality" of the connection- dependent on the channel quality and perceived by the end user, or as relevant to the particular service- is then of paramount importance in order to initiate the handover procedures.

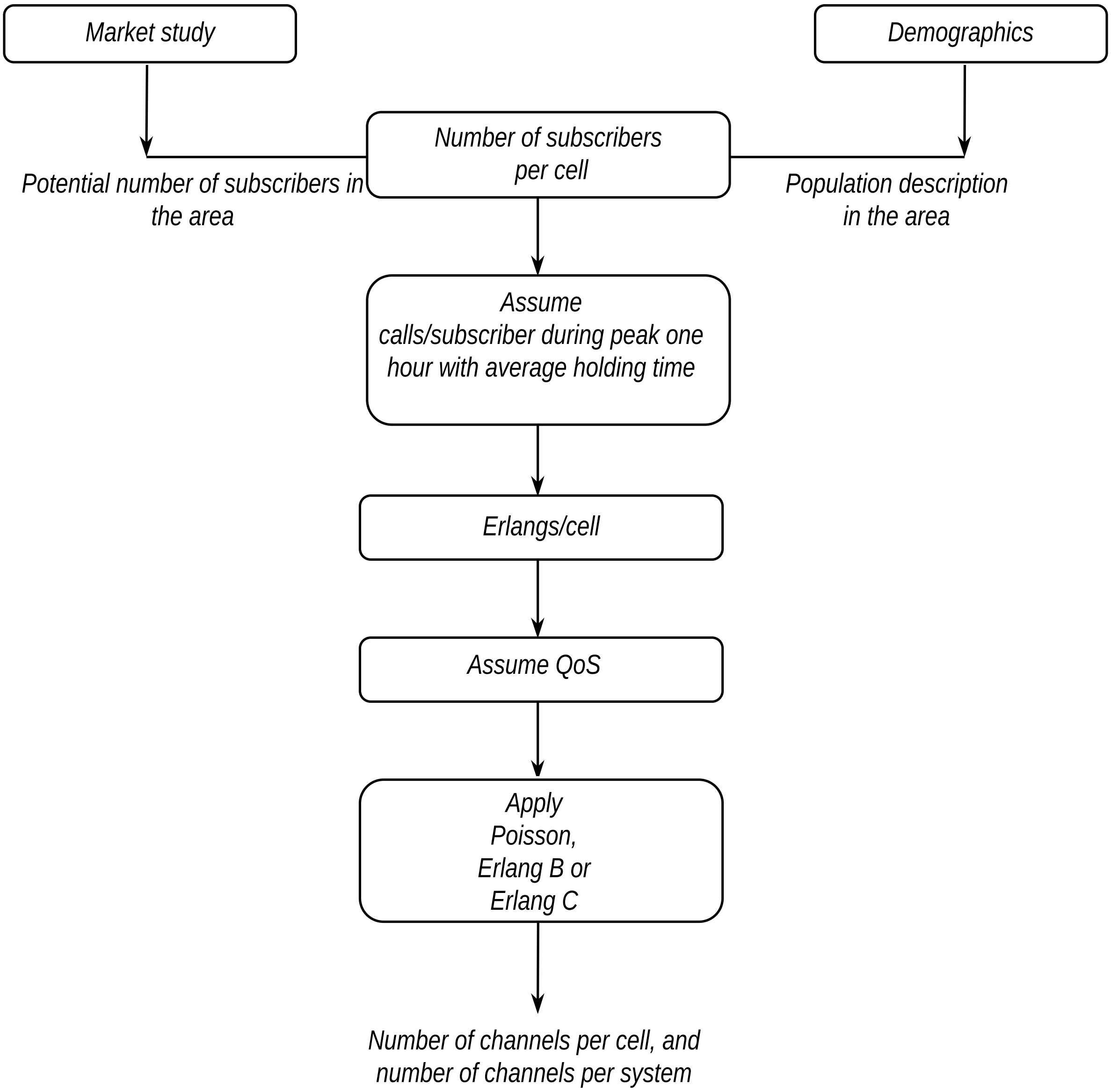


Figure 3.2 **:** Channelization of a cell and a wireless system.

3.1.2 Perceived Quality of Service

Two aspects unique to cellular systems are spectrum reuse and handover process. The former allows spectrum scarcity to be overcome; the latter combats channel quality degradation. Spectrum reuse and handover process are related in that the increase in the number of radio channels per unit area enabled by spectrum reuse is normally associated with an increase in the number of handover requests. To engineer radio resources, both the process characterizing the user demand and the handover process need to be considered. Since a failed handover request negatively affects user perception of service quality, and a connection cutoff due to unsuccessful handover is very annoying it relates to established connections, handover requests are normally handled with some form of priority over calls. Hence, a trade-off exists between spectrum reuse, call blocking, and handover failure. Assessing this trade-off is a typical task for traffic engineering of mobile systems.

A typical function of mobile systems is to monitor the channel quality and try to allocate a new channel (handover function) when the one in use no longer meets minimum quality requirements. Allocating a new channel call for almost immediate availability of radio resources and raises teletraffic problems which range from service prioritization to admission control. The channel quality is assessed by considering a range of metrics and depends on the service type [Gri96]. The "quality" of the connection - dependent on the channel quality and perceived by the end user, or as relevant to the particular service - is then of paramount importance in order to initiate the handover procedures.

According to the recommendations of *ITU-TSS*, [ITU89] Quality of Service, *QoS,* as it is perceived by users is determined by four quality factors (Fig. 3.3). One of them, service support, is determined by the organization of the telecommunication operator. The other factors depend on the network itself.

Service Support indicated how well a network operator or service provider is able to offer a service and to support its use.

Service Operability indicates how well a service is adapted to successful and easy application by a user.

Serviceability is an indication of the extend to which a user can obtain a service and retain it for the desired period. It depends on the ability of the network to handle a certain amount of traffic, on the availability of network elements and on the impact of phenomena on the transmission medium on reliability of the connection used by the service.

Service Integrity indicates the quality of signal transmission during service offering.

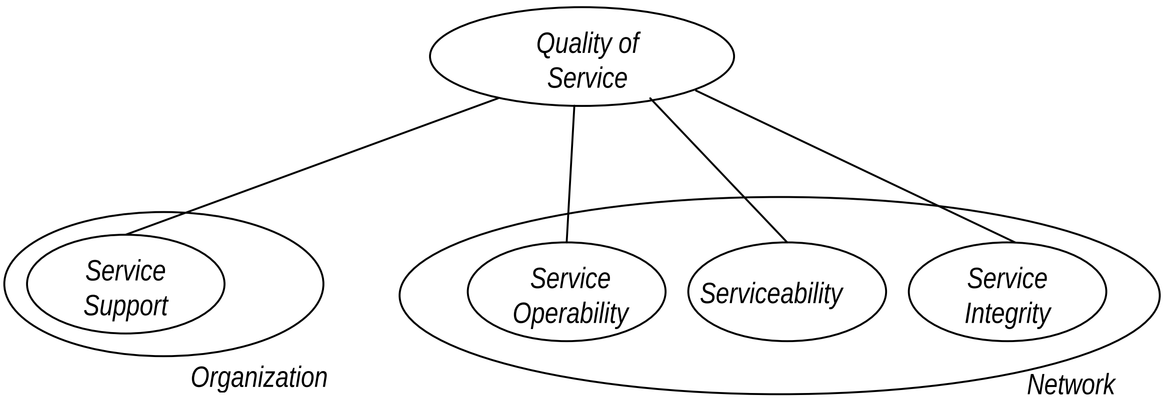


***Figure 3.3* :** Four quality factors determining Quality of Service.

When quality of two different options for a wireless personal network has to be compared (e.g., differing in base station locations or base station parameter settings) it is impractical to have to use all quality parameters mentioned above. It is much more practical to work with a universal quality parameter in which all quality parameters of speech services are contained. Therefore can be proposed a Quality of Service Index (*QoS-Index*) as a quality parameter. It is composed of a Serviceability component G_{sb} an a Service Integrity component G_{si} :

$$I_{QoS} = w_{si}\, G_{si} + G_{sb}\ . \tag{3.4}$$

In this composition w_{si} is the weight of the Service Integrity component, and G_{si} is called Grade of Service Integrity. In most cases one will find Service Integrity more important than Serviceability. Therefore w_{si} will have a value greater than one. The Grade of Service Integrity is given by:

$$G_{si} = \Pr\left[\frac{t_{lq}}{t_{call}} > \alpha_{lq} \vee N_{HO} > f_{HO,\max} t_{call}\right]. \tag{3.5}$$

In this expression:

t_{call} is the call duration,
t_{lq} is the summation of periods of insufficient speech quality ($FER > FER_{max}$),
N_{HO} is the number of handovers during a call with duration t_{call},
α_{lq} is the maximum allowable fraction of call duration during which quality is insufficient,
$f_{HO,max}$ is the maximum allowable frequency of handovers.

The Grade of Serviceability is given by:

$$G_{sb} = w_{naf}\, \Pr_{naf} + w_{suf}\, \Pr_{suff} + w_{cf}\, \Pr_{cf} + w_{ctf}\, \Pr_{ctf}\ . \tag{3.6}$$

In this expression:

$\Pr_{naf}$ is the probability of failing or long lasting network access ($t_{na} > t_{na,max}$),
$\Pr_{suf}$ is the probability of failing or long lasting call setup ($t_{su} > t_{su,max}$),
$\Pr_{cf}$ is the probability of connection failure,
$\Pr_{ctf}$ is the probability of failing or long lasting call termination ($t_{ct} > t_{ct,max}$).

Parameters w_{naf} , w_{suf} , w_{cf} , and w_{ctf} are the weights of corresponding probabilities in the Grade of Serviceability. These weights indicate that some quality parameters are more important than others. Indicative values for all weights and parameters are given in Tab. 3.1. When these values for weights and parameters are used the *QoS-Index* will have values between 0 (excellent quality) and 20 (very bad quality). The exact parameters values are a choice for the network operator. They are a compromise between quality and cost of network installation.

Table 3.1 **:** *QoS-Index*. Indicative values for weights and parameters.

Weight	***Value***	***Parameter***	***Value***
w_{si}	20	FER_{max}	0.04
w_{naf}	2	$t_{na,max}$	10s
w_{suf}	2	$t_{su,max}$	5s
w_{cf}	20	$t_{ct,max}$	2s
w_{ctf}	1	α_{lq}	0.1

3.2 Mobile User Calling Behavior

An important issue influenced by user mobility concerns the mobile user calling behavior expressed by the incoming/outgoing call arrival rate and average call duration. From fixed networks it is well known that different calling behavior characterizes business and residential users. In mobile communication systems, different calling patterns can be identified for ***moving*** and ***nonmoving*** users. For example, shorter call duration is expected for car drivers than for nonmoving users. In wireless/mobile networks the presentation of traffic is dependent on both time and space, with spatial dependence significantly more variable than in wired networks.

Very little is known about the traffic characteristics of personal communications wireless networks. However, on fixed telephone networks, traffic is modeled accurately. For current telephone usage, the mean call arrival rate and mean call duration during busy hours are 2,8 calls/hour and 2,6 min/call, respectively.

In mobile communication networks the teletraffic originating from the service area of the system can be described mainly by two traffic models which differ by their view of the network. *a)* The *traffic source model*, which is also often referred to as the *mobility model*, describes the system as seen by the mobile unit. The traffic scenario is represented as a population of individual traffic sources performing a random walk through the service area and randomly generating demand for resources, i.e. the radio channels. *b)* In contrast, the network traffic model of a mobile communication system describes the traffic as observed from the non-moving network elements, e.g. base stations or switches. This model characterizes the spatial and time-dependent distribution of the teletraffic. The traffic intensity λ is in general measured in call attempts per time unit and space unit (calls/sec.km^2). Taking additionally the mean call duration $E[t_{call}]$ into account, the offered traffic is $A = \lambda E[t_{call}]$ (in Erlang/km^2). This measure represents the amount of offered traffic in a defined area.

Both traffic models are used in mobile communication system design [Leu94], [Lam97]. Particularly the latter model is of principal interest when determining the location of the main facilities in a mobile network, i.e. the base stations and the switching centers. These components should be located close to the expected traffic in order to increase the system efficiency. Due to their capability to describe the user behavior in detail, *traffic source models* are usually applied for the characterization of the traffic in an individual cell of a mobile network. Using these models, local performance measures like *new call blocking probability* or *handover blocking probability* can be derived from the mobility pattern. Additionally, these models can be used to calculate the subjective quality-of-service values for individual users.

A call traffic model is needed, which generates call arrivals (i.e., calls initiated) for different classes of traffic and models time-varying user behavior. Each call traffic class should be characterized by its probability of occurrence, call arrival rate, mean call duration, and distribution.

Traffic engineering and capacity planing for a cellular radio system starts with a comprehensive analysis of the current traffic situation in the network on a cell-by-cell basis. The first issue to be considered is the time variation of the traffic. Figure 3.4 shows a typical example for the traffic intensity $A_i(t)$ in a radio cell Z_i over the hour of the day. Usually the network is dimensioned to offer a minimum grade of service *GoS* during the busy hour. The busy hour is defined as the 1-hour time span during a day which exhibits the large traffic, cf. Fig. 3.4, for planing purposes, the busy hour traffic is measured on a weekly basis with some averaging over the peak traffic days of the week. For cellular mobile systems, peaks usually occur between 10 a.m. and 12 a.m. with a second peak between 1 p.m. and 3 p.m. due to commercial and business users.

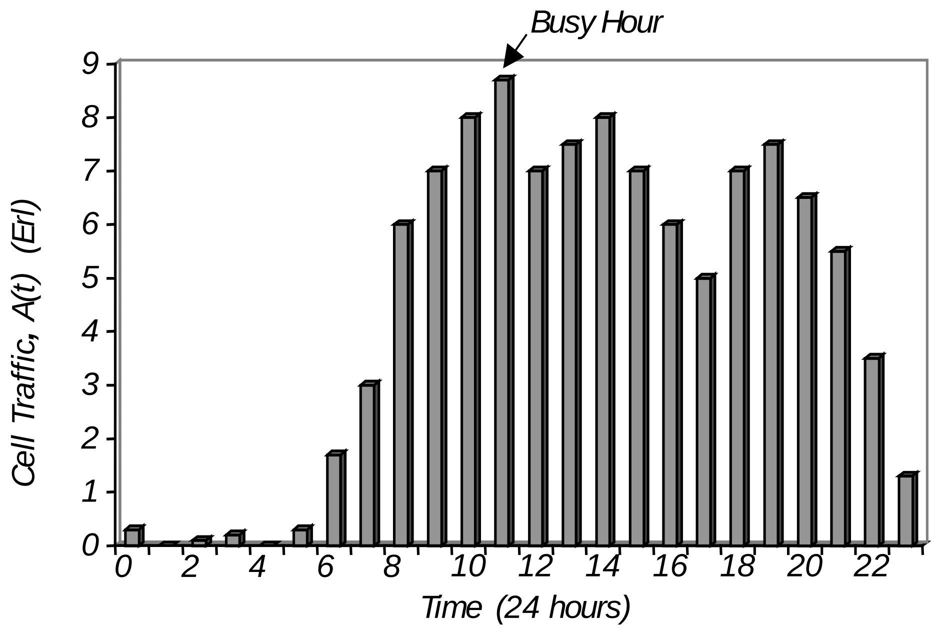


Figure 3.4 **:** Traffic over the hours of a day (1 cell) [Bai97].

It should be noted that the weekly busy hour traffic is still time variant, with seasonal variations and some overall growth rate. Figure 3.5 illustrates this for a single radio cell in the *GSM* network. In downtown areas the highest traffic usually occurs during the business hours, whereas in suburban regions the busy hour is expected to be in the evening.

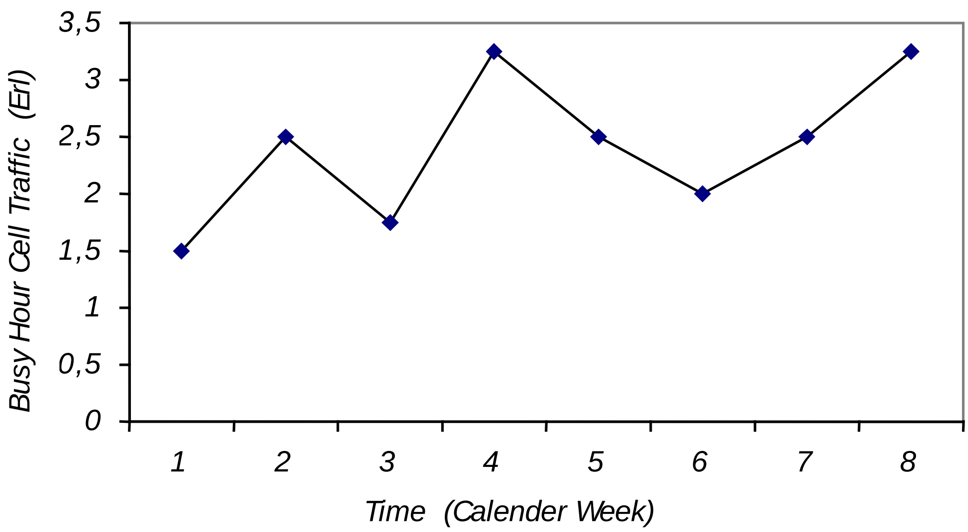


Figure 3.5 **:** Short-term development of busy-hour traffic [Bai97].

Time-of-day call traffic volume patterns can be investigated. Figure 3.6 shows the traffic volume patterns derived from mobile telephone call traffic data set collected by Phillips [Phi95].

Have been examined the averages over all days, weekdays (Mondays-Fridays), and weekends (Saturdays and Sundays).

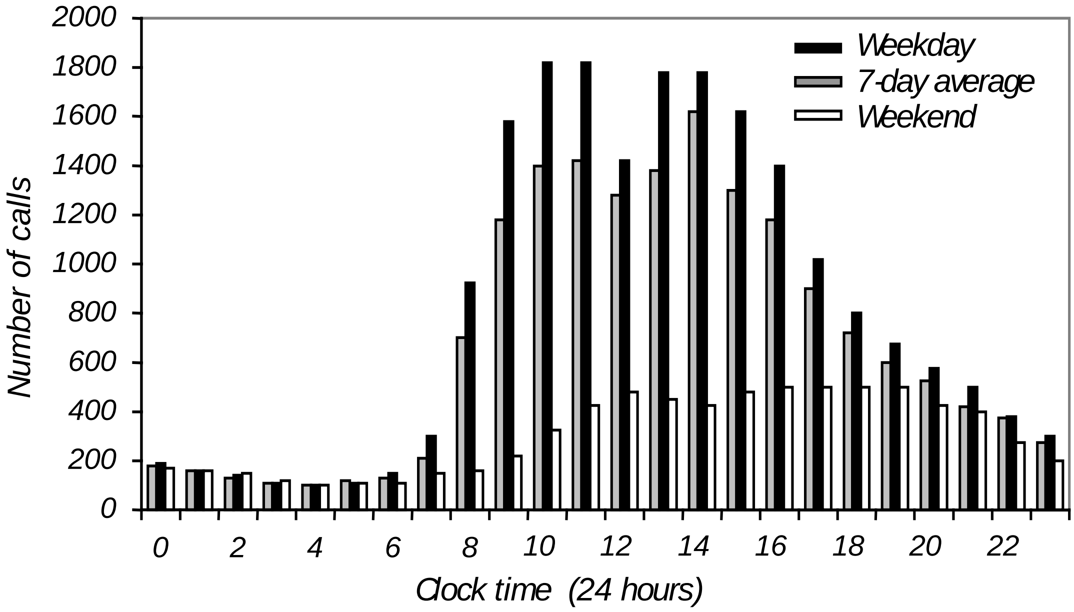


Figure 3.6 : Average number of call arrivals per hour.
(Average hourly call volume over 9 months) [Phi95].

It can be observed that there are essentially three periods of call activity during a typical weekday. The first corresponds to the late night period (12 a.m.-7 a.m.) when there is very little activity. The second is the peak period which spans the regular business hours (8 a.m.-4 p.m.). The last period is the corresponds to the off-peak period during the evening hours. One observation is that volume changes abruptly during the morning transition, but the evening transition is much more gradual.

The personal communications networks store important per-user information, such as current location, authentication information, and billing information, in *user profiles* [Dah98]. Data management refers to accessing and maintaining the information in user profiles. For example, during call setup, among other tasks, the network needs to access the callee's profile for location information and the caller's profile for authentication information. Also, the network registers user movements by updating location information in user profiles.

The callee distribution modeling characterizes how the callee is generated for each call. In reference [Lam97] have been developed a callee distribution model that models the behavior of each individual caller. It accounts for such real time behaviors as users calling a group of people (e.g., business associates and friends) more frequently. In this model, each user is associated with its own callee list. To obtain reasonable parameters, have been investigated empirical probability distributions using the notation of *callee rank*. The rank k callee of a caller is the caller's k^{th} most frequently called person within a reference period, Fig. 3.7.

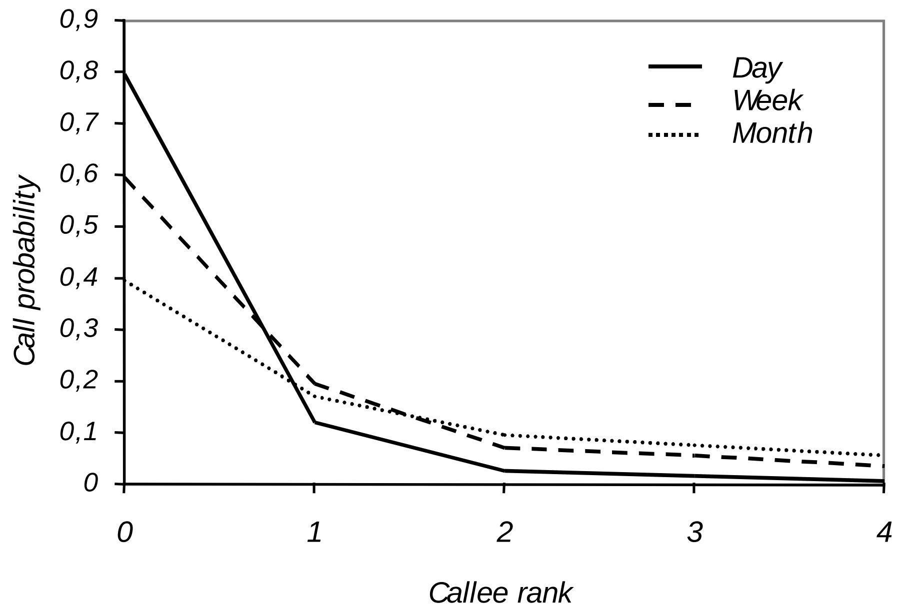


***Figure 3.7.*:** Mean call probability versus callee rank [Lam97].

Telephone calls are made by individual customers as they fit into their living habit or into the conduct of their business. The aggregated customers' calls follow varying patterns. Our goal in following two subsections is to present the basic teletraffic related parameters for nonmoving and moving users, respectively.

3.2.1 Nonmoving Users

Estimation can be based on relevant estimations from fixed networks [Meh94], [Bai97]. The calls are characterized by rate of origination and by call holding time. It is customary to assume that each user originates his calls at random during his idle time and independently of al other users. This assumption cannot be strictly true. However, for large numbers of subscribers where each has a small probability of initiating a call, this restriction can be neglected. For calls arriving at random, the originating rates are calculated as follows [Jak94], [Aki93]. Consider a time span of t and divide it into n short time intervals Δt ($t = n\Delta t$), where Δt is short enough that only one call can occur in that period. Denoting call arrival rate by λ; then the probability that a call originates in the interval is $\lambda\Delta t$. Since random calls originate independently, the probability that k calls originate during the time t becomes:

$$\Pr[k] = \frac{(\lambda t)^k}{k!} e^{-\lambda t} \quad . \tag{3.7}$$

The above is termed the *Poisson arrival process*. This model is accurate for a large cellular communication system with many channels and many users with similar calling patterns [Rap96].

For telephone conversation, the probability distribution function of call holding time is well approximated by the exponential holding time, that is:

$$cdf_c(t) = \begin{cases} 1-e^{-\mu t} & t \geq 0 \\ 0 & t < 0 \end{cases} . \tag{3.8}$$

The average call holding time is given by

$$E[t_c] = \int_0^{\infty} t.cdf^{'}(t)dt = \frac{1}{\mu} . \tag{3.9}$$

The close connection between the Poisson arrival process and the exponential call duration time can be exploited immediately in discussing properties of the negative-exponential distribution (Appendix C). The exponential model for service time distribution carries with it the memoryless property used as one of the defining relations of the Poisson process. This property will be used implicitly in a number of places in this work.

3.2.2 Moving Users

We now summarize the traffic statistics of cellular systems reported in [Hac81], [Meh94]. Estimation can be based on the following assumptions:

- The rate of outgoing calls of a specific service type depends on the user mobility class (e.g., pedestrian, car passenger). This is due to the fact that the mobile user class affects the convenience of initiating calls to a user. For example, compared to a user situated in this office, a pedestrian will normally initiate a lower number of voice calls and even lower number of (if any) fax calls.
- The rate of incoming calls does not depend on the user mobility class, since the calling mobile user in general ignores the current moving state of the called mobile user.
- The call duration is strongly affected by the user mobility class. This is due to the fact that the mobility class determines the user convenience for making longer calls (e.g., shorter call duration's are expected for metro passengers compared to private car passengers).

The convenience of communicating (by means of call initiation and call duration) is assumed to be affected by the user mobility class according to the hierarchy listed in Tab. 3.2. Note that the higher the corresponding value is expected.

Table 3.2 : The hierarchy of user mobility classes.

Call initiation	***Call duration***
Nonmoving business	*Nonmoving residential*
Nonmoving residential	*Nonmoving business*
Car passenger	*Car passenger*
Public transportation passenger	*Pedestrians*
Pedestrians	*Public transportation passenger*

Figure 3.8 depicts the percentages of moving (passengers, pedestrians) and nonmoving users vs. time in an typical European city, i.e. Athena [Mar97]. Once we know the average call holding time for all classes of users, the average holding time for cellular users can be estimated.

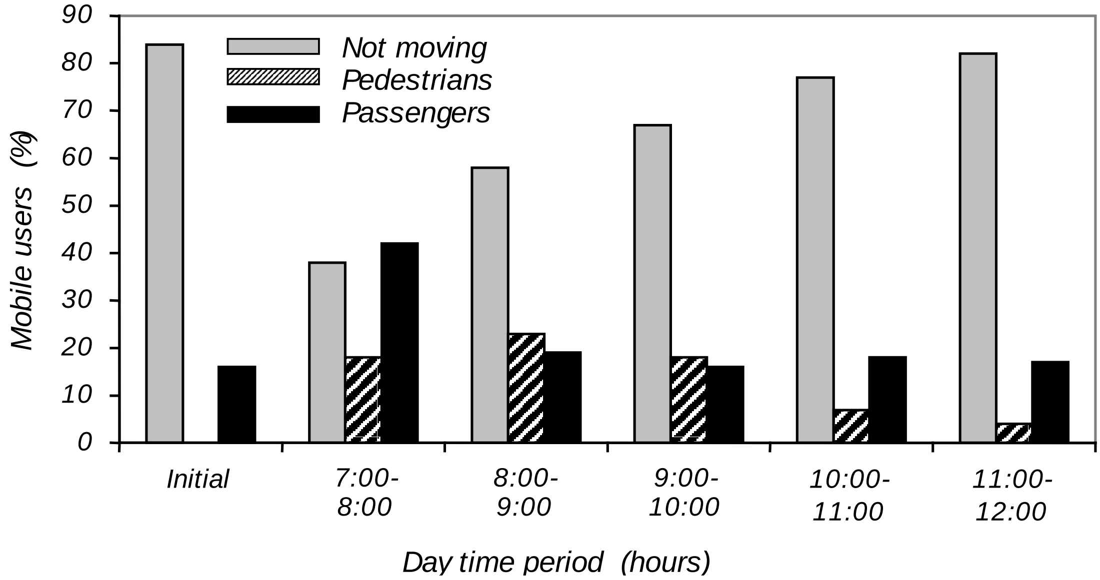
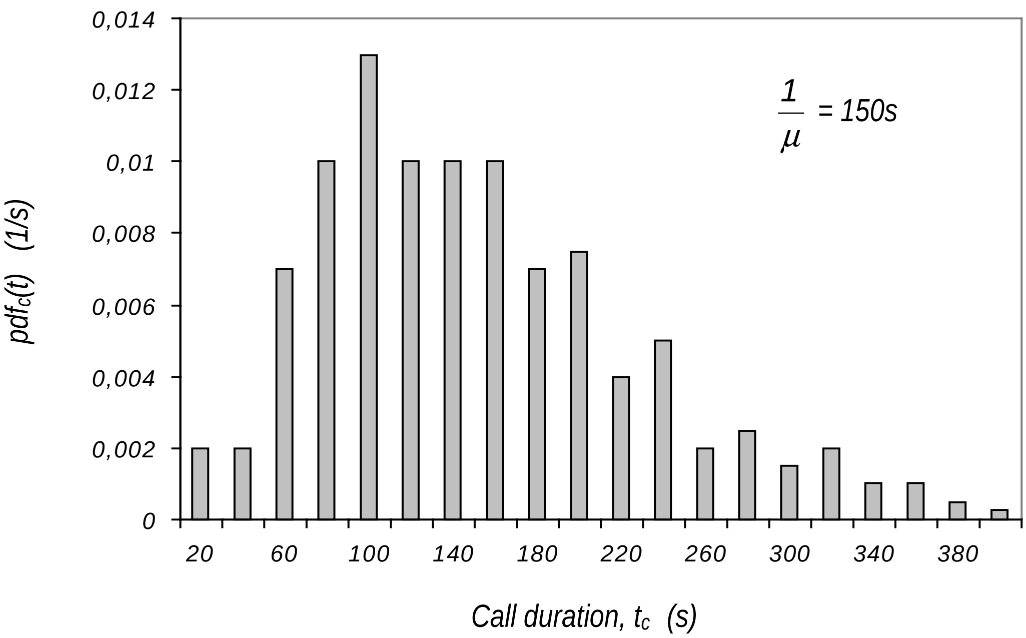
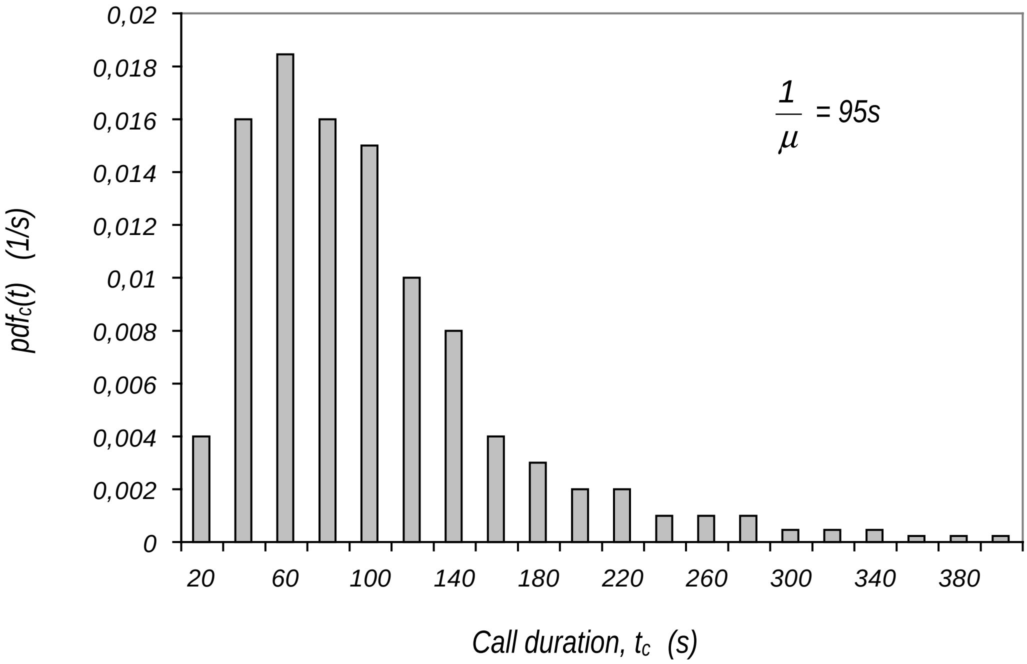


Figure 3.8 : Percentages of moving (passengers, pedestrians) and not moving users versus day time period [Mar97].

The traffic characteristics of pedestrians, car drivers, and public transport passengers have been measured in several large cities of Canada [Hac81]. The call duration distribution for these three classes of moving users are shown in Fig. 3.9:



a)



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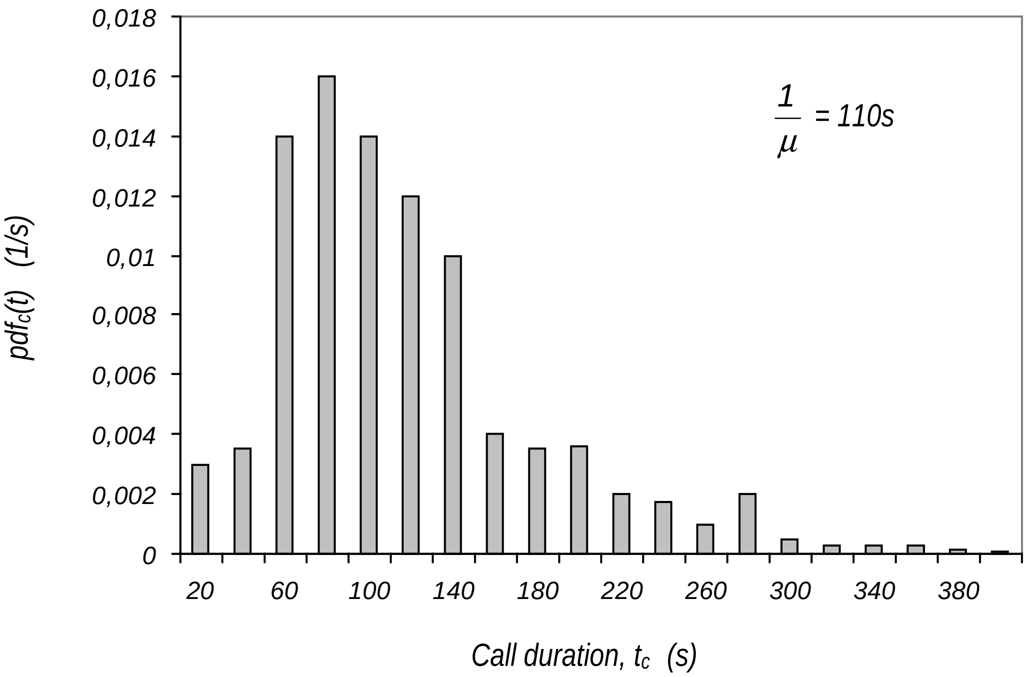

c)

Figure 3.9 **:** Probability density function of the call duration for different classes of users: a) pedestrians; b) car drivers; and c) public transport passengers [Hac81].

Based on these measurements, the following range of traffic numbers can be recommended for the cellular communications systems:

- Average call duration: t_c = 95-150s.
- Traffic per subscriber during busy hour of the busy month: A_i = 0.02-0.04Erl.

The traffic per subscriber during the busy hour will decease as the system matures, and as the system users increase the use of system during off-peak hour.

However, user call traffic and the sum of call- and mobility-related signaling traffic are not immediately correlated, and may show different busy hours (Fig. 3.10).

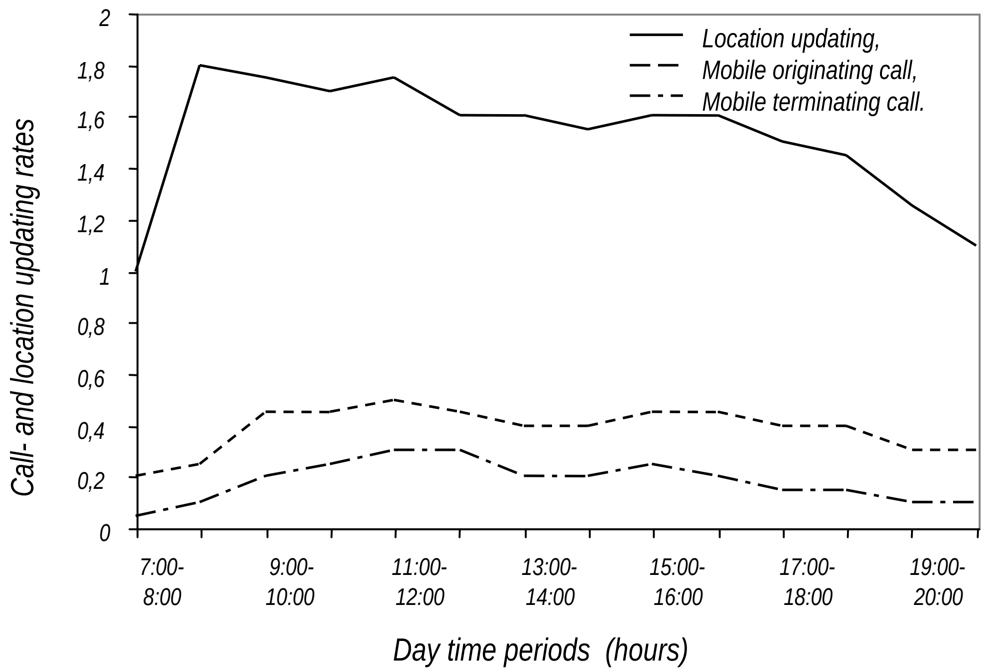

Figure 3.10 **:** Call- and mobility-related signaling rates per mobile user [Bra97].

3.2.3 Mobility and Teletraffic-Models Integration

In order to model various scenarios of user mobility and teletraffic we propose the following procedure using the above proposed teletraffic and mobility (Chapter 2.3) models. Computer simulations aim to obtain statistical estimates of the mobile boundary crossings and all other related parameters in an environment where the mobiles are allowed to move freely with randomly varying velocities and directions within realistic environments. In order that this simulation model can be used in a variety of tasks, flexibility is provided in terms of its inputs and outputs, Fig. 3.11. As first the simulation frame work is defined. The objective of the simulation is to generate sufficient data to examine the boundary crossing probabilities and other related parameters as a function of cell size and shape, mobile user behavior and geographical environment. We also have to define relevant network performance parameters to be able to compare the design alternatives.

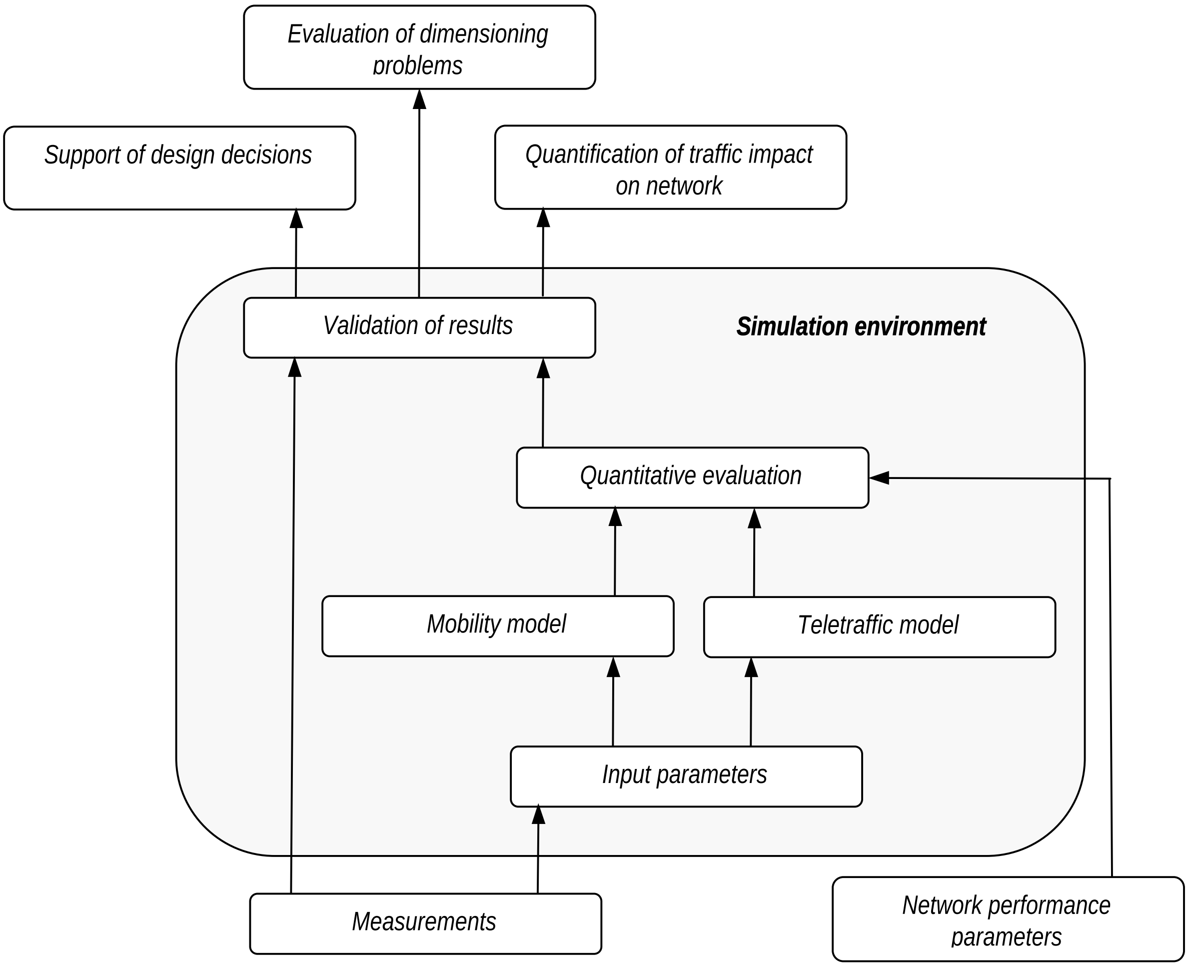

***Figure 3.11* :** Integrated simulation environment.

The main emphasis of the simulation is to reflect, as far as possible, a truly typical case. Therefore the simulation must incorporate a sufficiently large mobile population. This will minimize the influence of initial conditions and the variation of the stochastic processes. In the simulation tool (Fig. 3.11), a mobile population of 2,500 mobile users drives the statistics of the boundary crossing phenomena to reach the steady state condition. A uniform distribution is assumed for initial spatial location of the users [Gué88]. This assumption is valid, since in a cellular network, the relative orientation of streets in cells varies randomly, giving on the average an approximately uniform distribution of possible directions. However, a suitable selection of input parameters allows modification of this to fit any particular required pattern. Since the destination point of the mobiles can be any place in the coverage area, mobile users are allowed to move away from the staring point in any direction with equal probability. Depending on the structure of the cellular coverage area, a subscriber unit may move toward the destination point via different paths. However, in any case, the mobile direction should be biased towards the direction of its destination. The amount of deviation of a mobile user from its current direction at successive intervals is referred to relative angle changes after each crossroad. The probability distribution of the variation of the mobile direction along its path is taken in accordance with assumption in Chapter 2.3.2. The limits of the distribution are in the range of [$-\pi$, π) with respect to the current direction. The changes in direction occur in time steps that are street-length and speed depended. The motivation for this chose mobility modeling is based on the fact that the time of the last change in direction hardly provides any information about the time of next change in direction (rapidly changes of mobile velocity after each crossroad are very unlikely). However, the driver might be on his way to some remote location possibly involving immediate a change of velocity, for example, he might be looking for a parking space or a close-by address requiring multiple successive velocity changes. The speed of mobile units is chosen to be a realization of a random variable with probability density function as have been proposed in Chapter 2.3.3.2. The chose of such a modeling way seems reasonable since the more extreme the speed value, the less likelihood of its occurrence. This completes the presentation of the method used to represent the mobility behavior of all users.

We now proceed wit the description of the integration of models used for the mobility behavior and the teletraffic statistics. The assumptions made for the teletraffic statistics are very classical. Namely, the total call duration is taken to be exponentially distributed with different parameters for different user groups (with $1/\mu_{c,p}$ as mean call duration for pedestrians, $1/\mu_{c,c}$ for car passengers, and $1/\mu_{c}$ for non moving users, respectively). The arrival of new calls is assumed to be a Poisson process with parameter λ_p for pedestrians and λ_c for car passengers. We assume that the total service time and mobile motion are independent. Namely, the vehicle motion is taken to have no influence on the call duration. This ignores the possibility that people blocked in traffic jams might have longer communication times than the typical customer.

Different cal and mobility models can easily be incorporated. The simulated representation of a mobile originated or terminated call is based on the following procedure:

1. For each user class, at the time instant where a new or handover call is to be generated, a mobile is initialized according to the mobility model and spatial distribution assigned to the current scenario (e.g., uniform distribution within the cell for new calls, and uniform distribution over the cell border for handover calls, respectively). If more than one mobility models are assigned to that user class, one of them is chosen randomly with predefined probabilities.

2. All active mobile users are moved according to their assigned mobility model at each simulated time step.

3. Upon termination of its call, a mobile removed.

The aim of the refinement of the basic mobility and teletraffic models is to increase the accuracy of the estimated output parameters at minimum cost. Cost in this case may refer to computational cost (e.g., the computation time required by a simulation model) or real cost (e.g., corresponding to the cost of measuring the target parameters). In this context, the proposed simulation environment can be exploited for validation of theoretical assumptions, evaluation of analytical models, and system design decisions.

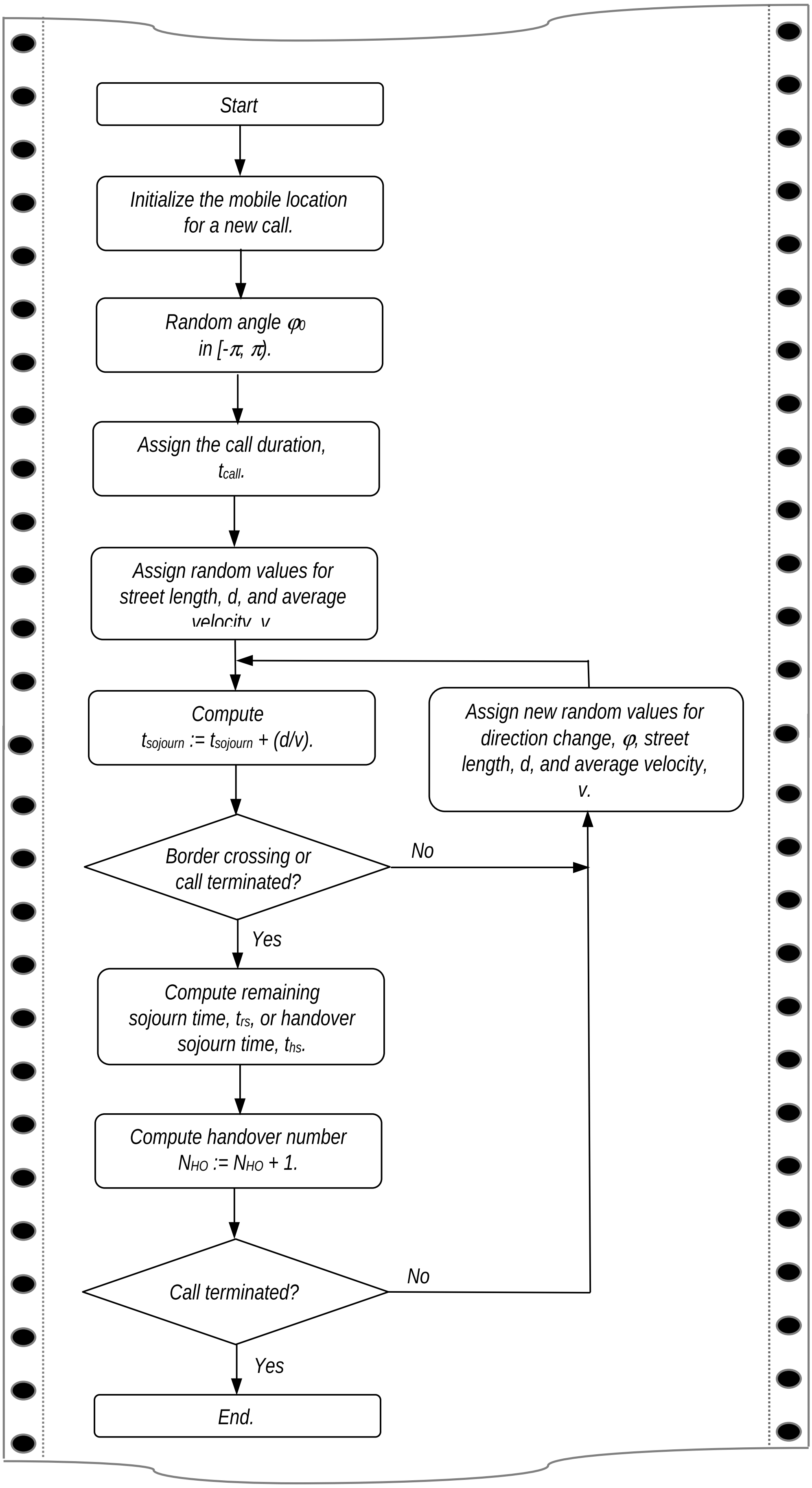

Figure 3.12 : Simulation flowchart for each mobile user.

3.3 User Sojourn Time

The time over which a call may be maintained within a cell, without handover, is called *sojourn time*, *residence time* or *dwell time*. The sojourn time of a particular user is governed by a number of factors, which include propagation, interference, distance between the subscriber and the base station, and other time varying effects. Even when a mobile user is stationary, ambient motion in the vicinity of the base station and the mobile can produce fading, thus even a stationary subscriber may have a random and finite dwell time. Analysis and measurements [Mar97], [Bai97], [Zee94] indicate that the statistics of sojourn time vary greatly, depending on the speed of the user and the type of radio coverage. For example, in mature cells which provide coverage for vehicular highway users, most users tend to have a relatively constant speed and travel along fixed and well-defined paths good radio coverage. In such instances, the sojourn time for an arbitrary user is a random variable with a distribution that is highly concentrated about the mean sojourn time. On the other hand, for users in dense, cluttered microcell environments, there is typically a large variation of sojourn time about the mean, and the sojourn times are typically shorter than the cell geometry would otherwise suggest. It is apparent that the statistics of sojourn time are important in the practical design of handover algorithms, (see Chapter 4.3).

Depending on whether a call is originated in a cell or handed over from a neighboring cell, two different cell sojourn times can be specified: (α) the new call cell sojourn time or call termination cell sojourn time, and (β) the handover call cell sojourn time, respectively. The first one, in the future called only *remaining sojourn time*, t_{rs} , is defined as the length of time a mobile terminal resides in the cell where the call was originated before crossing the first cell boundary or the cell where the call was terminated after crossing the last cell boundary. Similarly, the second one, in the future called *handover sojourn time*, t_{hs} , is the time spent by a mobile in a given cell to which the call was handed over from a neighboring cell before crossing to another cell (Fig. 3.13). The remaining sojourn time t_{rs} , and the handover sojourn time t_{hs} are two random variables whose distributions are to be found.

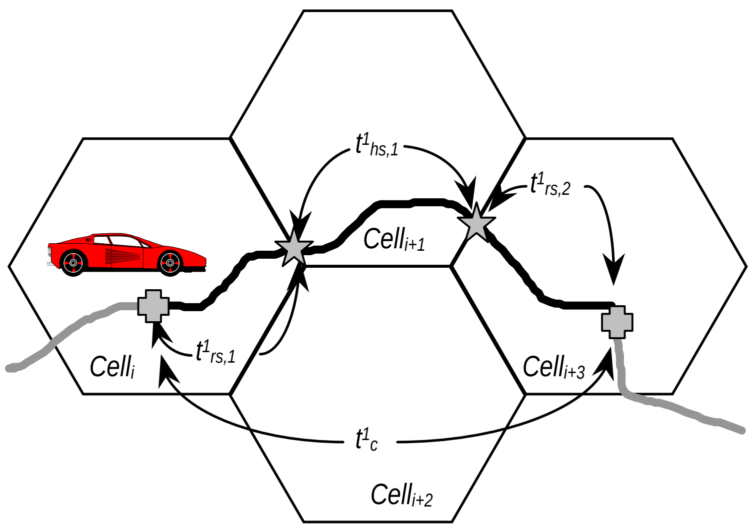

Figure 3.13 **:** Illustration of sojourn time, t_s , and channel occupancy time, t_{ch}.

Let us denote the unencumbered call duration by the random variable t_c . As shown in Fig. 3.13, a call, t^1_c , comprises successive sessions $t^1_{rs,1}$, $t^1_{hs,1}$, $t^1_{rs,2}$ in cells traversed by a mobile terminal. Let us denote the time spent in a cell by a user in communication prior to a handover (or subsequent handover) attempt or call completion by t_{ch} . This is just the channel occupancy time in a cell.

The computer simulation bases on the in Chapter 2.3 proposed mobility model aims to obtain statistical estimates of the mobile boundary crossings and the corresponding sojourn times in an environment where the mobile is allowed to move freely with randomly varying velocities and directions within realistic bounds. In order that this simulation model be used in a variety of tasks, flexibility is provided in terms of its inputs and outputs. The objective of the simulation is to generate sufficient data to examine the cell sojourn times statistic as a function of cell size, environment and user behavior.

The main emphasis of the simulation is to reflect, as far as possible, a truly typical case. Therefore the simulation must incorporate a sufficiently large mobile population. This will minimize the influence of initial conditions and the variation of the stochastic process. In this simulation, a mobile population of 2,500 drives the statistic of the boundary crossing and cell sojourn time phenomena to reach the steady state condition. A uniform distribution is assumed for spatial location of users. This assumption is valid, since the cellular network, the relative orientation of streets varies randomly, giving on the average an approximately uniform distribution of possible directions. However, a suitable selection of input parameters allows modification of this to fit any particular required pattern. Since the destination point of the mobiles can be any place in the coverage area, mobiles are allowed to move away from the starting point in any direction with equal probability. Therefore, a uniform distribution in the range $[-\pi, \pi)$ will be suitable for the initial mobile direction.

Distribution models such as exponential distribution, Erlang distribution, and gamma distribution have been used to approximate the distributions of cell sojourn times using data from field tests [Bar98], [Jed96], [Kha96]. We wish also to test the hypothesis that the cell sojourn time statistic follows a particular distribution. Following [Law91], we proceed with the generalized gamma distribution which provides a series of probability density functions, (Appendix A). Depending upon the values of its parameters, the gamma distribution can be shaped to represent many distributions as well as shaped to fit sets of measured or simulated data.

When fitting theoretical distributions to empirical data a common practice is to compare the corresponding theoretical and empirical probability density functions. Visual examination of the histogram deviation from the superimposed curve is a very convenient way to judge whether a fit is satisfactory. Although commonly used, this approach is very questionable from the point of view of statistical formalism. The normalized histogram (empirical probability density function) is obtained from the frequency histogram related to the collected data. The binwidth Δx is a crucial histogram parameter. We can get different histogram shapes varying from a "ragged" one for a small binwidth to a "block-like" one if Δx is large.

Figure 3.14 illustrates how significantly the binwidth selection Δx affects the histogram shape. Figure 3.14 a) corresponds to $\Delta x=1s$ reflecting in the most natural way the measurement resolution. In Fig. 3.14 b) the binwidth has been increased to $10s$. The range of the vertical axis in Figs. 3.14 a)-b) is the same to simplify comparison. It is seen from the figures that for $\Delta x=10s$ the histogram is much smoother. It is obvious that the choice of the binwidth Δx is critical for the qualitative analysis. What is the optimal value of Δx ?

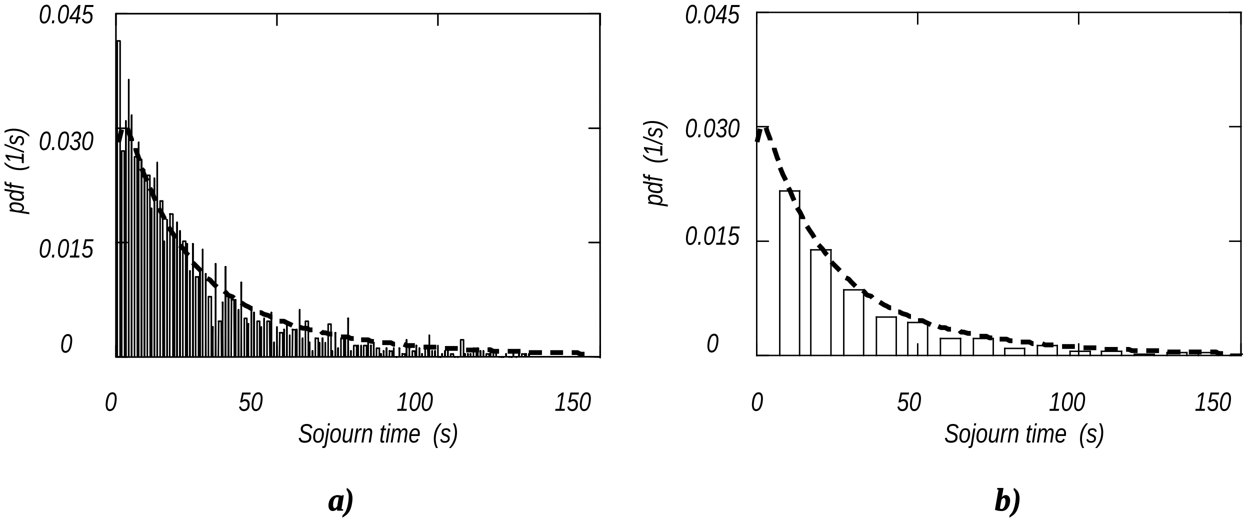

Figure 3.14 **:** Illustration of the signification of the binwidth selection.
a) $\Delta x = 1s$, b) $\Delta x = 10s$.

Several rules have been suggested for choosing the number of histogram intervals k. The best known of them is Sturges' rule [Law91] according to which

$$k = \lfloor 1 + \log_2 n \rfloor = \lfloor 1 + 3.322 \log_{10} n \rfloor \tag{3.10}$$

where n is the number of data samples in the data set and $\lfloor \bullet \rfloor$ denotes the largest integer number not greater than the argument. However, the resulting histograms are "block-like". The data have been overaggregated and the true underlying density is masked. Law and Kelton [Law91] are very skeptical about the usefulness of such rules in general. They recommend trying several different values of interval width Δx and choosing one that gives a "smooth" histogram. Because this is a matter of subjectivity, goodness-of-fit can not be evaluated based on the probability density function analysis. Another more sophisticated approach is needed.

A better option is to analyze an empirical cumulative distribution function instead of a histogram. Empirical cumulative distribution function statistics measure the discrepancy between an empirical cumulative distribution function and a hypothesized one. They enable goodness-of-fit evaluation that eliminates subjectivity.

The *Kolmogorov-Smirnov* goodness-of-fit test is frequently presented in the literature. The *Kolmogorov-Smirnov* goodness-of-fit test avoids the problems related with the bin size Δx present in the Chi-Square goodness-of-fit test, for example. This test provides two figures of statistical interest, the modified *Kolmogorov-Smirnov* distance D and the level of significance α. The lower (higher) D (α) is, the better the fit will be. This is what will allow us to establish a ranking among those fitting distributions that pass the *Kolmogorov-Smirnov* goodness-of-fit test with a certain level of significance. The level of significance α can be easily obtained from D and the size of the sample n as follows:

$$D_n = \frac{D}{\sqrt{n} + 0.12 + \frac{0.11}{\sqrt{n}}} \ , \tag{3.11a}$$

$$\alpha = 10^{(\log 2 - 2nD_n^2)}. \tag{3.11b}$$

Have been seen that the results of the *Kolmogorov-Smirnov* goodness-of-fit test depend on the size of the sample. As the size of the sample is closer to 2,000 the best fit is easily distinguished. This is why the cell-crossing simulation samples used in this study have sized around 2,500.

The evaluation of the agreement between the distributions obtained by simulation and the best fitted generalized gamma distribution is done by using the *Kolmogorov-Smirnov* goodness-of-fit test. Given the generalized gamma distribution as the hypothesized distribution, the values of the parameters *a*, *b*, *c* are found such that the maximum deviation *D* is minimum. The maximum deviation shows the biggest divergence between the observed and the hypothesized distributions.

$$\begin{aligned} D &= \max|cdf_\Gamma(t) - cdf_{rs}(t)| \quad \forall(t>0),\\ D &= \max|cdf_\Gamma(t) - cdf_{hs}(t)| \quad \forall(t>0), \end{aligned} \tag{3.12}$$

where $cdf_\Gamma(t)$, $cdf_{rs}(t)$, $cdf_{hs}(t)$ represent probability distribution functions of the generalized gamma, remaining and handover sojourn times, respectively.

Figure 3.15 illustrates the probability density function of the remaining sojourn time, t_{rs}, and handover sojourn time, t_{hs}, for passengers obtained by simulation and the equivalent generalized gamma function with a 0.05 level of significance. (The simulation-parameter values have been set as follow: $w_{-90°}$ = 0.75, $w_{90°}$ = 0.5, $w_{180°}$ = 0.0625, σ_φ = 0.125π; $\bar{d}$ =100m, σ_d = 100m, Rice-distributed; w_{mr} =1.25, $\bar{v}$ = 10km/h, $\bar{v}_{mr}$ = 45km/h, σ_v = 10km/h).

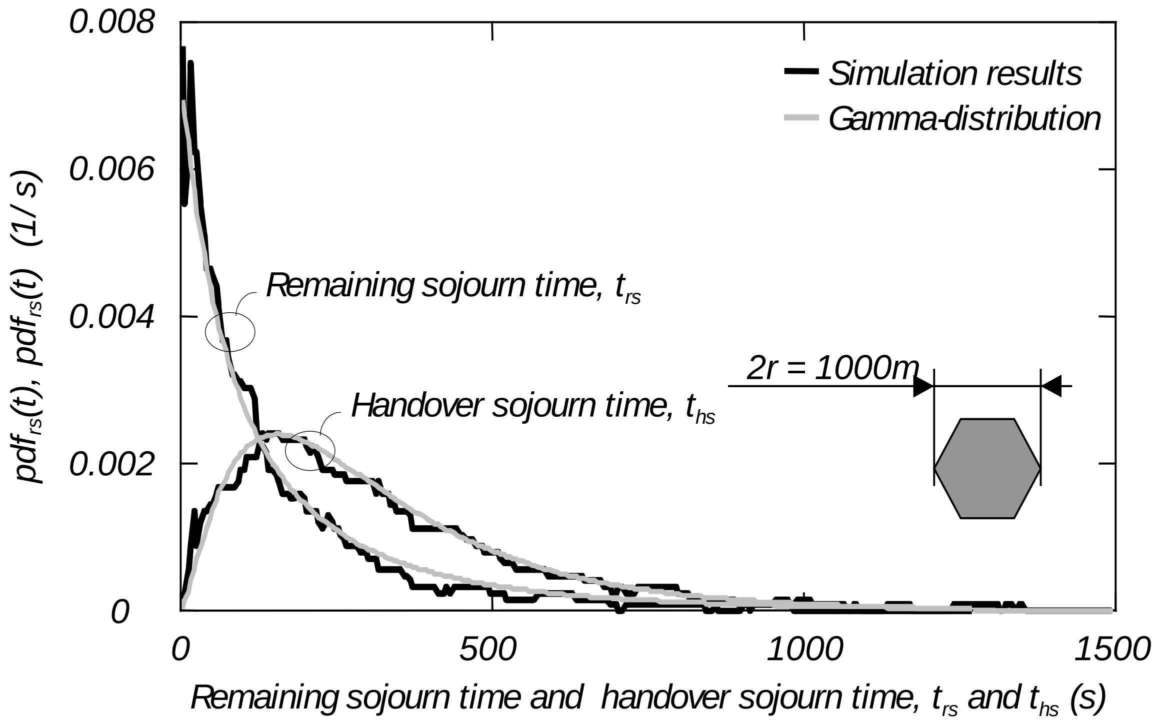

Figure 3.15 : The probability density functions of remaining sojourn time and handover sojourn time for a hexagonal cell for passengers.

Figure 3.16 illustrates the probability density function of the remaining sojourn time, t_{rs}, and handover sojourn time, t_{hs}, for pedestrians obtained by simulation and the equivalent generalized gamma function with a 0.05 level of significance. (The simulation-parameter values have been set as follow: $w_{-90°}$ = 0.5, $w_{90°}$ = 0.5, $w_{180°}$ = 0.125, σ_φ = 0.25π; $\bar{d}$ = 50m, σ_d = 40m, Rayleigh-distributed; w_{mr} =0, $\bar{v}$ = 4.6km/h, $\bar{v}_{mr}$ = 0km/h, σ_v = 3.7km/h).

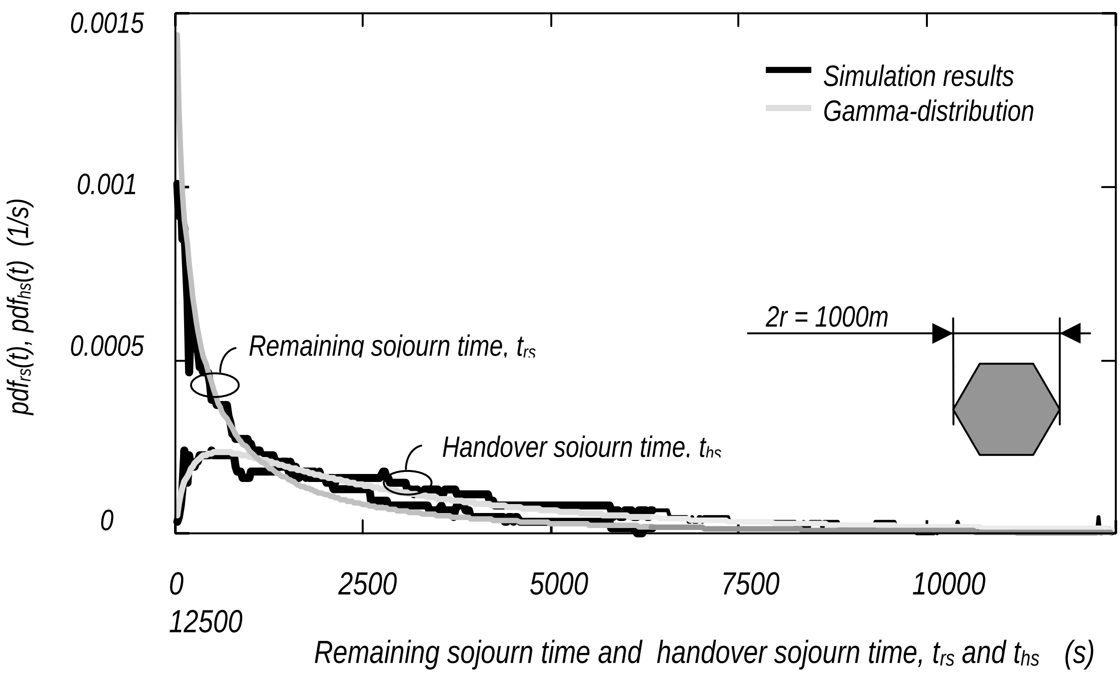

Figure 3.16 **:** The probability density functions of remaining sojourn time and handover sojourn time for a hexagonal cell for pedestrians.

Table 3.3 shows the values of *a*, *b*, *c* for the remaining sojourn time and handover sojourn time with a 0.05 level of significance for passengers and pedestrians, respectively. It can be observed that the value of *b* is independent of user behavior. A lot of simulation trials show that *b* is dependent from the mean call holding time and the ratio between mean velocity and cell size.

Table 3.3 **:** Best fitted gamma distribution parameter values for the remaining sojourn time and handover sojourn time.

	Remaining sojourn time			Handover sojourn time		
	a	b	c	a	b	c
Passengers	2.45	25	0.5	4.75	25	0.625
Pedestrians	3.5	25	0.325	5.75	30	0.375

The mean remaining sojourn time, $E[t_{rs}]$, and mean handover sojourn time, $E[t_{hs}]$, can be found by the following relations:

$$\overline{t_{rs}} = E[t_{rs}] = \int_0^\infty t\, pdf_{rs}(t)dt \ ,$$
$$\overline{t_{hs}} = E[t_{hs}] = \int_0^\infty t\, pdf_{hs}(t)dt \ . \qquad (3.13)$$

The results for both kinds of users, passengers and pedestrians, respectively are summarized in Table 3.4:

Table 3.4 **:** Mean remaining sojourn time and mean handover sojourn time for passengers and pedestrians.

	Mean remaining sojourn time $E[t_{rs}]$ *(s)*	*Mean handover sojourn time* $E[t_{hs}]$ *(s)*
Passengers	*167*	*340*
Pedestrians	*1812*	*3658*

The sojourn time distribution is wheel dependent from the shape and size of the cell. Figure 3.17 shows the remaining sojourn time and handover sojourn time for a 120° sectorized umbrella cell (all simulation settings are similar as in the case of passengers). The sector makes up one third of a cluster comprising seven hexagonal cells (each with r =500m). It is also shown that the cell shape is related to the computed times, t_{rs} and t_{hs}.

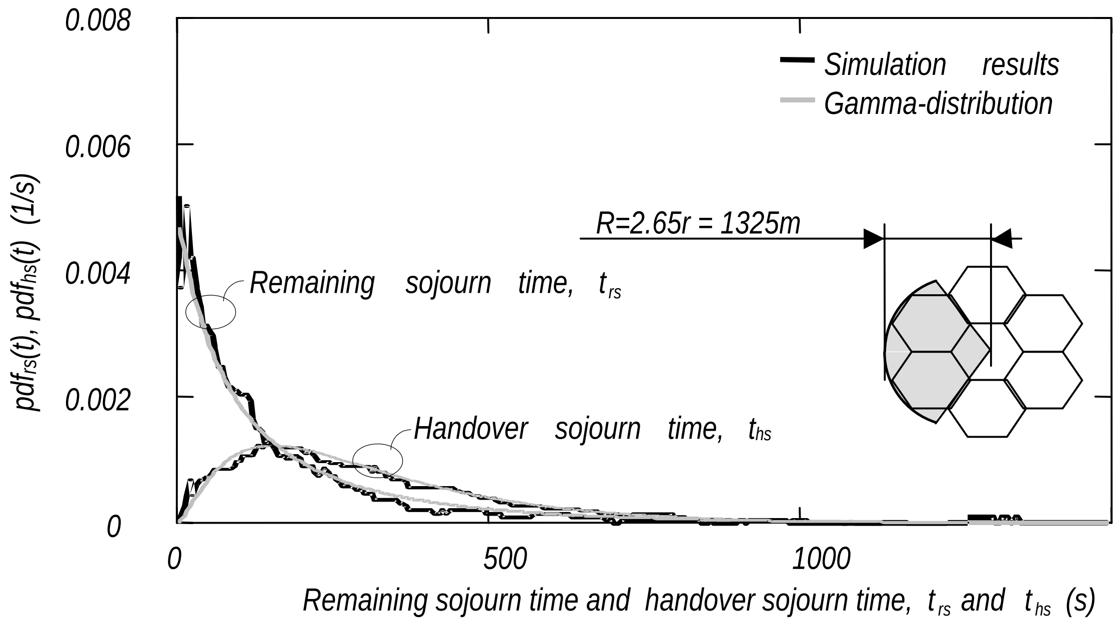

Figure 3.17 **:** The probability density functions of remaining sojourn time and handover sojourn time for a 120° sectorized cell for passengers.

Cell enlargement leads to a growth of sojourn times. Table 3.5 compares the calculated mean remaining sojourn times and mean handover sojourn times, $E[t_{rs}]$ and $E[t_{hs}]$ of hexagonal cells (r =500m and r =250m, respectively) with corresponding 120° sectorized umbrella cells.

Table 3.5 **:** Mean remaining sojourn time and mean handover sojourn time.

	Mean remaining sojourn time $E[t_{rs}]$ (s)	*Mean handover sojourn time $E[t_{hs}]$ (s)*
Hexagonal cell, r=250m	*65*	*134*
Sectorized cell, R=662.5m	*135*	*268*
Hexagonal cell, r=500m	*171*	*344*
Sectorized cell, R=1325m	*345*	*695*

The user sojourn time depends strongly from the user mobility behavior. The slow move the users the low is the value of mean sojourn time. Figure 3.18 shows the probability distribution function of the handover sojourn time for a cellular system for different percentages of slow moving users (pedestrians) and fast moving users (car and public transportation passengers).

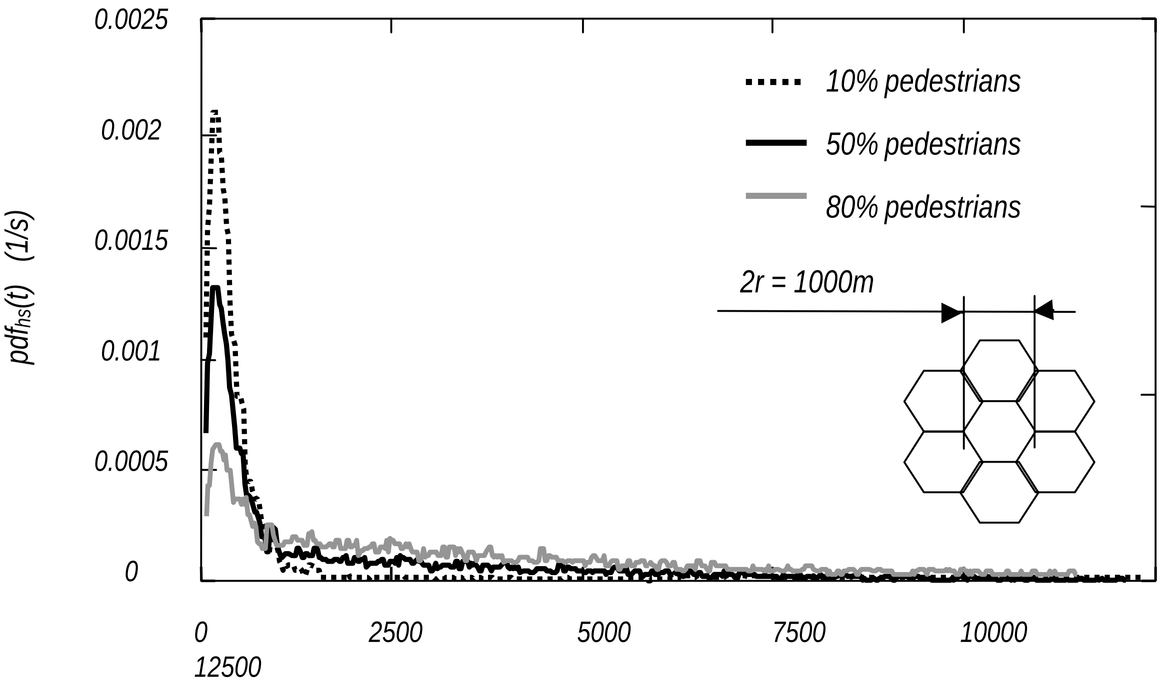

Figure 3.18 **:** The probability density functions of handover sojourn time for urban cellular systems as a function of pedestrians penetration.

When the effects of shadow fading are accounted for in order to modelize an actual cellular environment, the sojourn time distribution depends on the sequence of signal levels that the mobile terminal receives from it current basis station. On this basis, the propagation characteristics have been to included to the mobility ones. However, a mobility modeling under shadowing effects is only possible if the mobility model is based on the city plan (e.g., the mobile terminals are continually traced trough the streets).

3.4 Handover Rate

A mobile user can move through several cells while being involved in a call. The number of times a mobile crosses different boundaries during a call is a random variable dependent on the cell size, call holding time, and mobility parameters. Each handover requires network resources to reroute the call through a new base station. It is preferred to have as few handovers as possible in order to alleviate the switching load and to decrease the processing required in the system. The number of handovers has a lower bound which is equal to the number of boundary crossings a mobile undergoes.

A great advantage of mobility modeling is that it allows easily statistics computation for the number of handovers occurring during a call. As an example Tab. 3.6 shows the N_{HO}-th handover probability during a call. In this simulation is assumed that the call duration time is exponential distributed with mean value 120s and the cells are hexagonal with a diameter of 1000m.

Table 3.6 **:** Handover probability for a vehicle-born call.

Number of handovers N_{HO}	Handover probability $Pr[N_{HO}=0;1;2...]$
0	0.54
1	0.34
2 and more	0.12

For a cellular communication network, which subscriber penetration has a time-of-day period dependency and distribution as assumed in Chapter 3.2.2, (Fig. 3.8), the N_{HO}-th handover probability is also time-dependent (Tab. 3.7). The number of handovers will depend in first order on passengers penetration rate.

Table 3.7 **:** Handover probability for all calls.

Day time period (hours)	Handover probability		
	$Pr[N_{HO}=0]$ (%)	$Pr[N_{HO}=1]$ (%)	$Pr[N_{HO}=2...]$ (%)
Initial	92.6	5.4	2
7:00-8:00	78.8	16.1	5.1
8:00-9:00	88.5	9	2.5
9:00-10:00	90.8	7.2	2
10:00-11:00	91.1	6.7	2.2
11:00-12:00	91.5	6.3	2.2

Finally, Fig. 3.19 illustrates the dependency of the N_{HO}-th handover probability from the cell size. As can be observed, the average number of handovers per call decreases as the cell size increases.

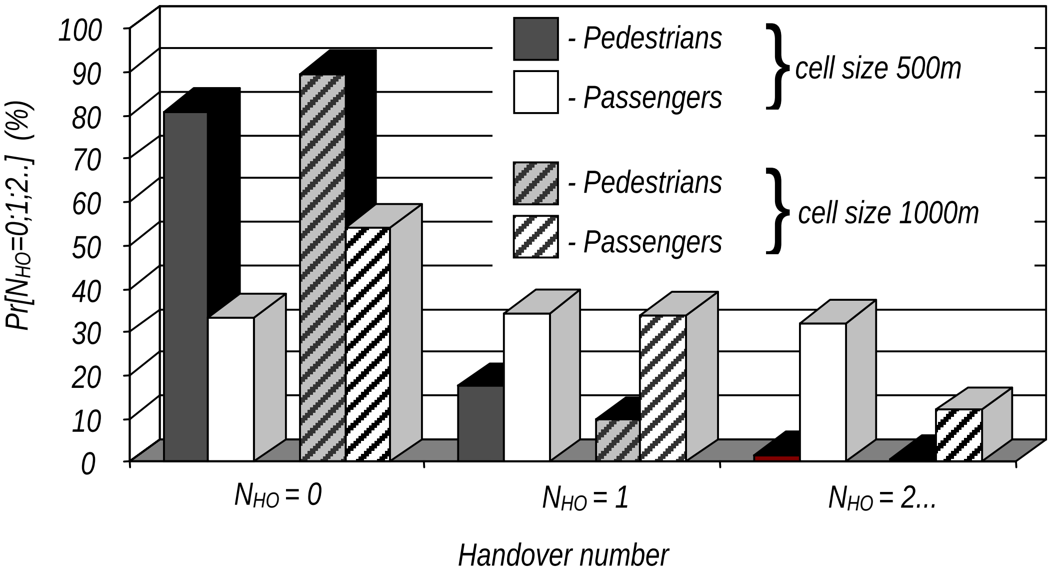

***Figure 3.19* :** Handover probability for different cell sizes.

As the number of handovers increases, the handover decision algorithms to be enhanced so that the perceived *QoS* does not deteriorate and the cellular infrastructure cost does not skyrocket. Here are presented two different methods to determine the average number of handovers in a cellular system.

Method I

The average number of times a nonblocked call is successfully handed over to the neighbor cell during the call, $E[N_{HO}]$, can be obtained from:

$$E[N_{HO}] = \sum_k k.\Pr[N_{HO} = k] \ , \tag{3.14}$$

where $\Pr[N_{HO}=k]$ is the probability that a nonblocked call has k successful handovers to the successive cells during its lifetime and N_{HO} is an integer random variable. Let $\Pr_{new}$ be the probability that a nonblocked new call will require at least one handover completion, let $\Pr_h$ denote the probability that a nonfailed handover call will require at least one more handover before completion, and let $\Pr_{h,fail}$ be the probability that a handover attempt fails. Then

$$\begin{aligned}
\Pr[N_{HO}=0] &= (1 - \Pr_{new}) + \Pr_{new}.\ \Pr_{h,fail}\ , \\
\Pr[N_{HO}=1] &= \Pr_{new}\ (1 - \Pr_{h,fail})(1 - \Pr_h + \Pr_h.\ \Pr_{h,fail})\ , \\
&\cdots\cdots \\
\Pr[N_{HO}=k] &= \Pr_{new}\ (1 - \Pr_{h,fail})[\Pr_h\ (1 - \Pr_{h,fail})]^{k-1}\ (1 - \Pr_h + \Pr_h.\ \Pr_{h,fail})\ .
\end{aligned} \tag{3.15}$$

Substituting (3.15) in (3.14) gives the average number of handovers per call as the following:

$$E[N_{HO}] = \frac{\Pr_{new}(1-\Pr_{h,fail})}{1-\Pr_{new}(1-\Pr_{h,fail})} \quad . \tag{3.16}$$

The value of $\Pr_{new}$ can be obtained by:

$$\Pr_{new} = \Pr[t_c > t_{rs}] = \int_0^\infty \Pr[t_c > t \mid t_{rs} = t]\Pr[t_{rs} = t]dt \quad . \tag{3.17}$$

t_{rs} is mainly dependent on the mobility of the users, and has no influence on the call duration t_c . Therefore

$$\Pr_{new} = \int_0^\infty \Pr[t_c > t]\Pr[t_{rs} = t]dt = \int_0^\infty [1-cdf_c(t)]pdf_{rs}(t)dt \quad . \tag{3.18}$$

where $cdf_c(t)$ is the cumulative distribution function of the call duration time.

Similarly, the value of $\Pr_h$ can be obtained by following equation:

$$\Pr_h = \Pr[t_c > t_{hs}] = \int_0^\infty [1-cdf_c(t)]pdf_{hs}(t)dt \quad . \tag{3.19}$$

Under the assumption that the call duration time follows a negative exponential distribution, the probability that any randomly selected call duration time will end in time duration t is:

$$\Pr[t_c = t] = cdf_c(t) = 1 - e^{-\mu_c t} \quad . \tag{3.20}$$

Therefore the values of $\Pr_{new}$ and $\Pr_h$ can be obtained by the following equations:

$$\Pr_{new} = \int_0^\infty e^{-\mu_c t}\, pdf_{rs}(t)dt \quad , \tag{3.21}$$

$$\Pr_h = \int_0^\infty e^{-\mu_c t}\, pdf_{hs}(t)dt \quad . \tag{3.22}$$

The values of $\Pr_{new}$ and $\Pr_h$ can be numerically evaluated by substituting a best fitted generalized gamma probability density function for pdf_{rs} and pdf_{rs} in (3.21) and (3.22), respectively.

Method II

The random variables t_{rs} and t_{hs} are assumed to be independent and identically distributed with general probability density functions of $pdf_{rs}(t)$ and $pdf_{hs}(t)$. The Laplace-Stieltjes transform of $pdf_{hs}(t)$ can be given as:

$$L[pdf_{hs}(t)] = PDF_{hs}(s) = \int_0^\infty pdf_{hs}(t)e^{-st}dt = E[e^{-st}] \quad . \tag{3.23}$$

From the excess life theorem or residual service time [Kle75], the Laplace-Stieltjes transform
of $pdf_{rs}(t)$ can be obtained as following:

$$L[\,pdf_{rs}(t)] = PDF_{rs}(s) = \frac{1}{s.E[t_{hs}]}\left[1 - PDF_{hs}(s)\right] \;. \tag{3.24}$$

The number of handovers experienced by a call depends on the call duration time (which are assumed as exponentially distributed), and can be obtained as follows [Nan93]:

$$E[N_{HO} \mid t_{rs,1}, t_{hs,1}, t_{hs,2}, ...] = 1.\int_{t_{rs,1}}^{t_{rs,1}+t_{hs,1}} \mu_c e^{-\mu_c t} dt + 2.\int_{t_{rs,1}+t_{hs,1}}^{t_{rs,1}+t_{hs,1}+t_{hs,2}} \mu_c e^{-\mu_c t} dt + 3.\int_{t_{rs,1}+t_{hs,1}+t_{hs,2}}^{t_{rs,1}+t_{hs,1}+t_{hs,2}+t_{hs,3}} \mu_c e^{-\mu_c t} dt + ...$$

$$= \int_{t_{rs,1}}^{\infty} \mu_c e^{-\mu_c t} dt + \int_{t_{rs,1}+t_{hs,1}}^{\infty} \mu_c e^{-\mu_c t} dt + \int_{t_{rs,1}+t_{hs,1}+t_{hs,2}}^{\infty} \mu_c e^{-\mu_c t} dt + ... \tag{3.25}$$

$$= e^{-\mu_c t_{rs,1}}\left[1 + e^{-\mu_c t_{hs,1}}\left[1 + e^{-\mu_c t_{hs,2}}\left[1 + ... \right.\right.\right. \;.$$

Considering $E[E[N_{HO} \mid t_{rs,1}, t_{hs,1}, t_{hs,2}, ...]] = E[N_{HO} \mid t_{rs,1}]$ and using (3.23), equation (3.25) can be rewritten as follows:

$$E[N_{HO} \mid t_{rs,1}] = e^{-\mu_c t_{rs,1}}[1 + PDF_{hs}(\boldsymbol{\mu}_c)[\,1 + PDF_{hs}(\boldsymbol{\mu}_c)[1 + ...$$

$$= \frac{e^{-\mu_c t_{rs,1}}}{1 - PDF_{hs}(\mu_c)} \;. \tag{3.26}$$

Taking the expectation of (3.26) and considering (3.23) and (3.24), can be obtained the average number of times a nonblocked call is successfully handed over to the neighbor cell during the call as follows:

$$E[N_{HO}] = \frac{PDF_{rs}(\mu_c)}{1 - PDF_{hs}(\mu_c)} = \frac{1}{\mu_c E[t_{hs}]} \;. \tag{3.27}$$

In Tab. 3.8 is shown the average number of handovers per call for different cell sizes. This table compares the results obtained from Eqs. 3.16 and 3.27. Agreement of the two results is a justification of the proposed cell sojourn times distributions.

Table 3.8 **:** Mean number of handovers per call. Values obtained from Eq. 3.16 and (Eq. 3.27), respectively.

Cell size (m)	***Mean number of handovers $E[N_{HO}]$ (1/call)***	
	Pedestrians	***Passengers***
250	*0.41 (0.415)*	*1.89 (1.89)*
500	*0.21 (0.205)*	*0.98 (1.01)*
1000	*0.11 (0.095)*	*0.58 (0.58)*

In the last results, we have seen that: *a*)the handover rate increases as the square root of the increase in the cells per unit area; and *b*)the handover rate is very near approximated by the ratio of mean call duration to the mean cell sojourn time.

Figure 3.20 shows the mean number of handovers per call averaged over all mobile users. This figure contains results obtained in accordance with the assumptions related to Chapter 3.2. The large passenger's fraction (car drivers and public transport passengers, over 40%, see Fig. 3.20) is the reason why in the gap time from 7 a.m. through 8 a.m. the mean number of handovers per call is clearly over the values in other gap times. The results obtained indicate a good accordance with the measurement results from operating cellular networks [Bra97].

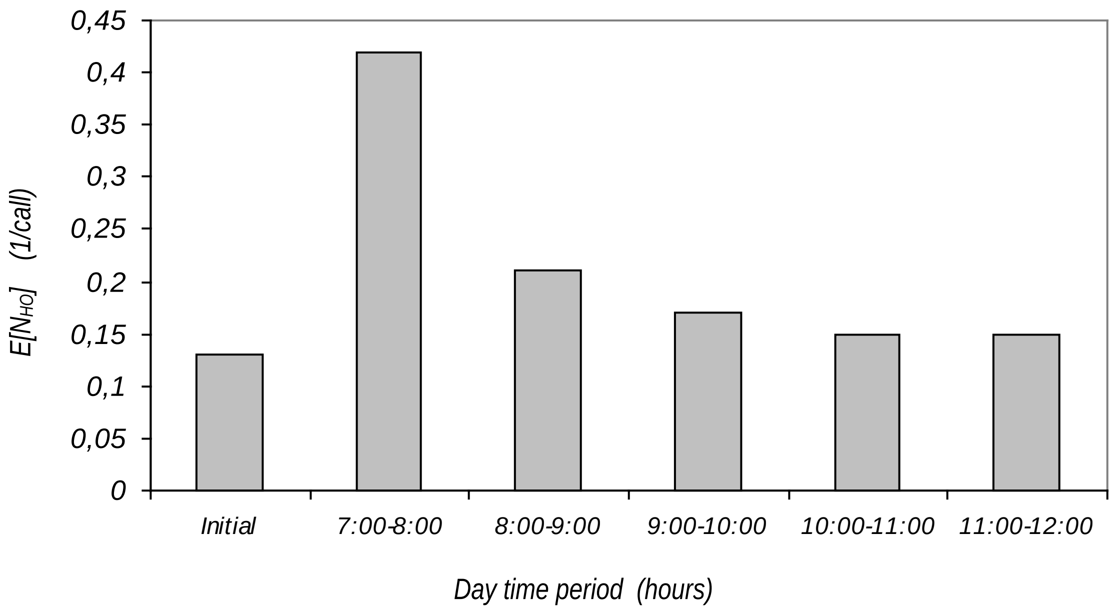

Figure 3.20 **:** Mean number of handovers per call for all users (cell size 500m).

In a wireless cellular system, the network time delay for a handover request is limited by a timeout period. If the network fails to respond within the timeout period, the handover call is forced terminated. A study of this effect on the performance (the call incompletion probability) of a wireless network is presented in Chapter 4.2.

3.5 Channel Holding Time

The channel occupancy time distribution has been studied quite extensively in the past for classical cellular systems. A common assumption in these studies has been that the call holding time (the time requested for a call connection) is exponentially distributed. The first traffic model for cellular mobile systems was proposed by Hong and Rappaport [Hon86], who analyzed the performance and showed that the channel occupancy time distribution could be approximated by the exponential distribution when the call holding times are exponentially distributed. Using a simulation model, Guerin [Gue87] showed that, for the mobile users with "low" change rate of direction of the movement, the channel occupancy time distribution displays a rather poor agreement with the exponential distribution fitting. In other words, most analytical studies in the literature assume that the channel occupancy times are exponentially distributed. However, recent field studies [Bar98], [Jed96], [Jor97] showed that the channel occupancy times are not exponentially distributed for cellular systems. Therefore, further investigation on channel occupancy times is needed.

The channel holding (or occupancy) time is a random variable defined as the length of time starting from the instant a channel in a cell is seized by the arrival of either a new or a handover call, until the time the channel is released either by completion of the call or by handing over to another cell. In conventional telephone systems, handover does not occur, and the channel holding time, t_{ch}, is equal to the call duration, t_c , i.e., follows negative exponential distribution. By contrast, in a cellular mobile network a call may experience a number of handovers with the result that the channel holding time becomes a fraction of the total call duration. Since the channel holding time is the minimum of the sojourn time, t_s, and the call holding time, t_c. When a new call is setup, a channel is occupied until the call is competed in the originating cell or the mobile moves out of the cell. Therefore, channel holding time of the new call, $t_{ch,new}$, is either the remaining sojourn time, t_{rs}, or the call duration time, t_c , whichever is less (Fig. 3.21 a)):

$$t_{ch,new} = \min\,(t_{rs}\,,\, t_c)\,. \qquad (3.28)$$

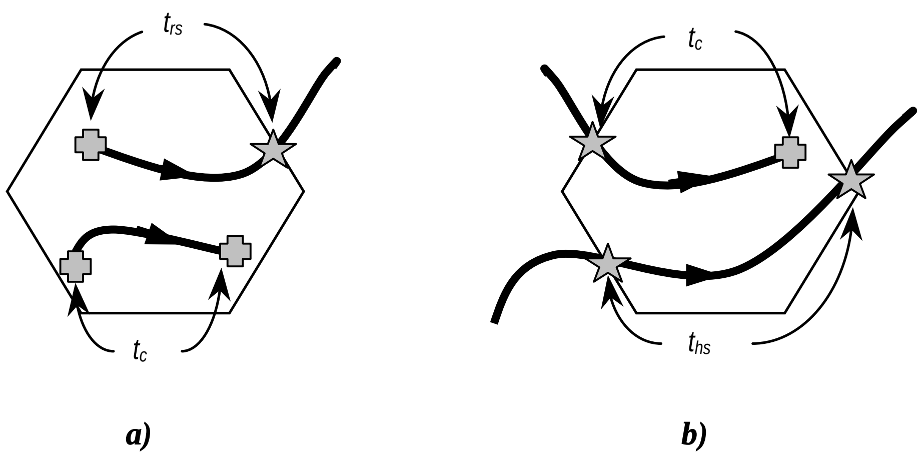

Figure 3.21 **:** Illustration of the new and handover call cell sojourn time.

A similar reasoning applies to the call which has been handed over from the neighboring cell. In this case, the channel is occupied until the call is completed or the mobile moves out to another cell (Fig. 3.21 b)). Therefore, the remaining duration of the call which is handed over from a neighboring cell can be stated as:

$$\left(t_c - t_{rs} - \sum_{i=0,1,\ldots} t_{h,i} \right) \Big| \left(t_{rs}, \forall t_{h,i} \right) \qquad (3.29)$$

where $t_{h,i}$ is the time duration of i^{-th} handover. Due to the memoryless property of the exponential distributions (Appendix C), the time remaining for a call after handover has the same distribution as the original call duration, t_c . Hence, the random variable shown in (3.29) can be replaced by t_c . Therefore channel holding time of the handover call, $t_{ch,h}$, is either the handover sojourn time, t_{hs}, or the call duration time, t_c , whichever is less:

$$t_{ch,h} = \min(t_{hs}, t_c) . \tag{3.30}$$

Since the remaining sojourn time, t_{rs} , and the handover sojourn time, t_{hs} , are mainly dependent on the physical movement of the user, and has no influence on the total call duration, t_c , it is reasonable to assume that the random variables t_{rs} and t_{hs} are independent of t_c . Therefore, the cumulative distribution function of $t_{ch,new}$ and $t_{ch,h}$ can be calculated by:

$$cdf_{ch,new}(t) = cdf_c(t) + cdf_{rs}(t) - cdf_c(t).\ cdf_{rs}(t) , \tag{3.31}$$

$$cdf_{ch,h}(t) = cdf_c(t) + cdf_{hs}(t) - cdf_c(t).\ cdf_{hs}(t) . \tag{3.32}$$

The distribution of the channel holding time in a given cell is a weighted function of $cdf_{ch,new}(t)$ and $cdf_{ch,h}(t)$. If ζ is the fraction of the average nonblocked new calls out of the average total number of calls in a cell, the fraction of the average number of successful handed over calls will be 1- ζ. Therefore, distribution function of the sojourn time including both new and handover calls will be:

$$cdf_{ch}(t) = \zeta\, cdf_{ch,new}(t) + (1 - \zeta) cdf_{ch,h}(t) . \tag{3.33}$$

ζ can be expressed in terms of the average number of handovers per call $E[N_{HO}]$ as

$$\zeta = \frac{1}{1 + E[N_{HO}]} . \tag{3.34}$$

Equation (3.33) can be rewritten in terms of the cell sojourn time and call duration time distributions as

$$cdf_{ch}(t) = cdf_c(t) + \zeta\left(1 - cdf_c(t)\right)\left(cdf_{rs}(t) + \frac{1-\zeta}{\zeta} cdf_{hs}(t)\right). \tag{3.35}$$

A numerical solution to (3.35), assuming t_{rs} and t_{hs} with a generalized gamma distribution, indicates that the distribution function of the channel holding time in a cell follows an exponential distribution. Figure 3.22 shows the probability density function of channel holding time for a hexagonal cell with diameter of 1000m. The same figure shows a comparison of the exponential distribution with the same average value as that of t_{ch} . It can be seen that the channel holding time distribution fits well with the exponential distribution. This agrees with the empirical data collected in cellular communication systems [Chl97]. Other field studies [Jed96], [Jor97], [Bar98] reveal that the exponential distribution shows a poor fit with the empirical data. A mixture of lognormal distributions are proposed. This can be true only in case if have been considered the total amount of calls over all users groups include speech and data-transfer services. Furthermore, the exponential model is probably not well adapted to systems where the average time between changes of direction is large when compared to the average service time. This can be case if cell radius is small, such as in a dense downtown environment. This suggests that mobile communications network designers have to carefully consider the distribution model for cell sojourn time and channel holding time for each cell in order to meet the better system optimization strategy.

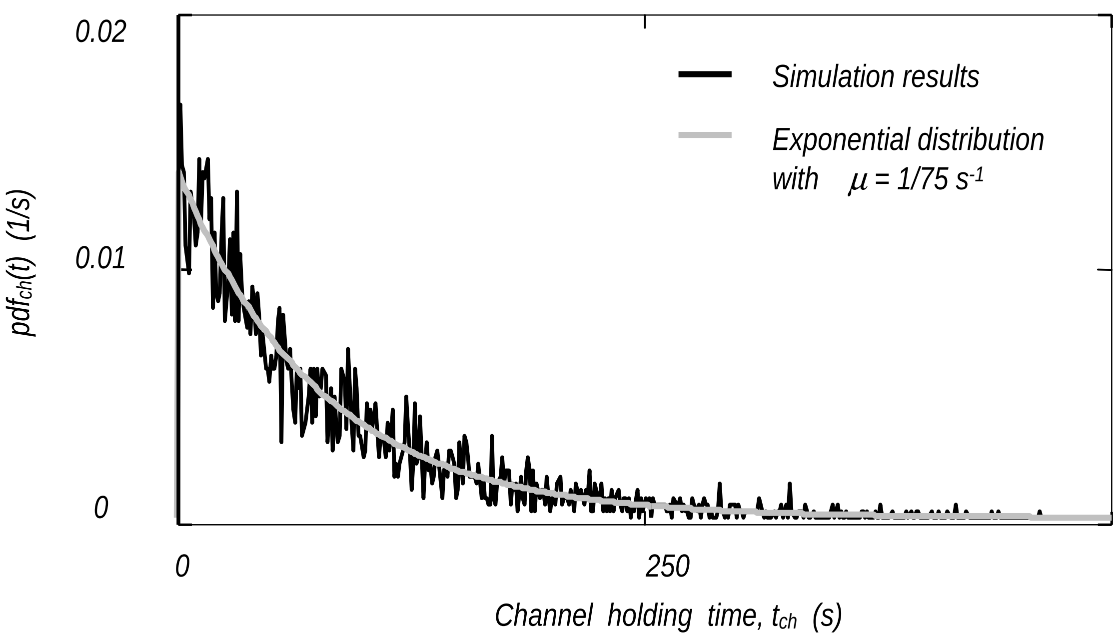

Figure 3.22 **:** Probability density function of channel holding time.

The channel holding time is a function of cellular system parameters such user mobility, cell size, and average call holding time. Data for the channel holding time distributions with a variety of cell structure and user mobility are available from the results of the mobility modeling discussed earlier.

Figure 3.23 compares the cumulative distribution functions of channel holding time for a system with hexagonal cells (r=500m) in two cases. The first one if all users are pedestrians, and the second one if all users are fast moving (car drivers and public transport passengers), respectively. In both cases the call duration time is assumed as exponential distributed with mean value μ_c=120s. A very close agreement between the distribution of channel holding time and call duration time is observed for pedestrians with increasing of the cell radius.

In order to observe how "close" the exponential approximations can be, have been to determine which exponential distribution function should be chosen. It is known that an exponential distribution is uniquely determined by its expected value. It is reasonable to use the exponential distribution whose expected value is equal to the real expected value of channel holding time. The are many criteria to evaluate this approximation. A good choice will be distance between the distribution functions of the simulation data and the exponential data. Hong and Rappaport [Hon86] proposed the following measure for the goodness-of-fit:

$$GoF = \frac{\int_0^\infty |\,cdf_{ch}(t) - (1 - e^{at})\,|\,dt}{2\int_0^\infty (1 - cdf_{ch}(t))dt} \tag{3.36}$$

where $cdf_{ch}(t)$ is the cumulative distribution function of simulated data and a is the expected value of the exponential distribution used for the approximation. This measure is the normalized accumulated difference of distribution functions.

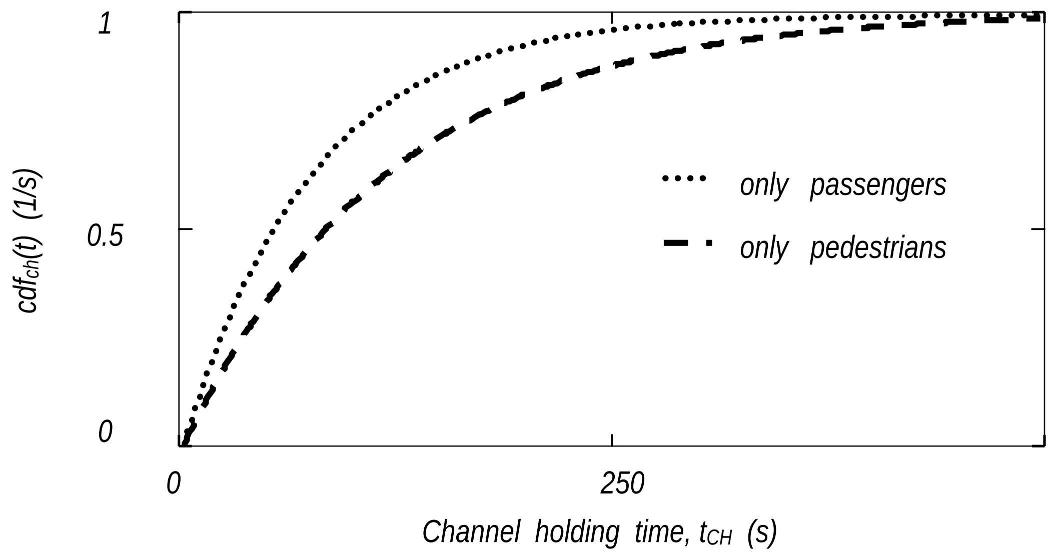

Figure 3.23 : Cumulative distribution function of channel holding time for all moving users.

The increasing of the penetration rate of slow moving and non moving users in the cellular environment leads to increase the mean channel holding time, $E[t_{ch}]$. The results are illustrated in Fig. 3.24 and Fig. 3.25, respectively. From Fig. 3.24, can be observed that the channel holding time is weak sensitive to the variance of penetration rate of pedestrians versus passengers. A more significant influence should be haven the penetration rate of non moving users.

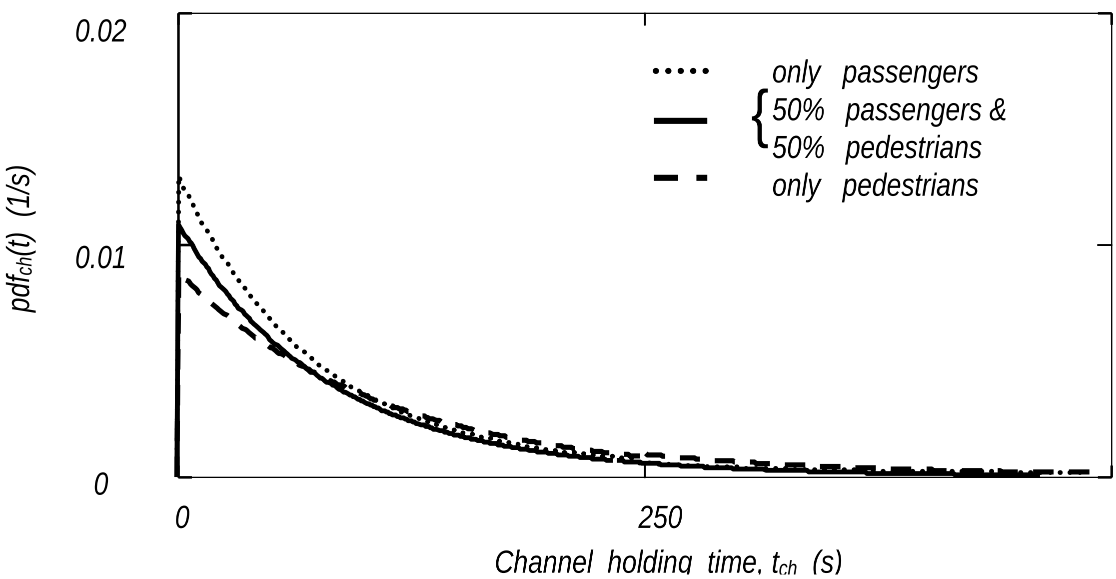

Figure 3.24 : Probability density function of channel holding time for all moving users.

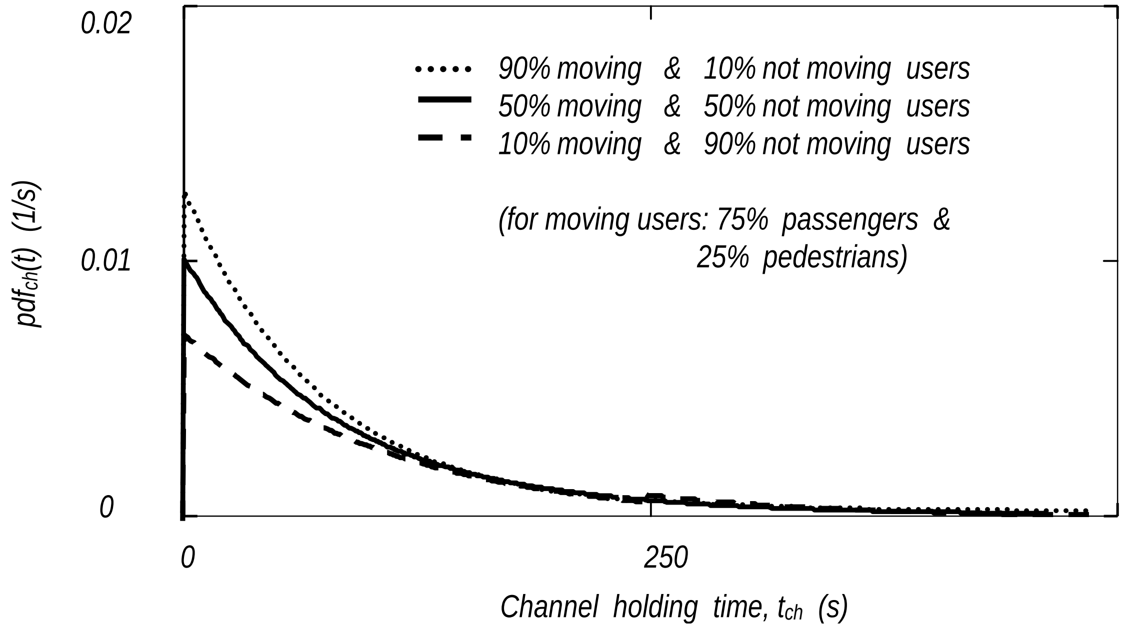

Figure 3.25 **:** Probability density function of channel holding time for all users.

The mean channel holding time for a cellular communication network under the assumption for user penetration rates made in Chapter 3.2 is showed in Fig. 3.26. The large fraction of high-mobility users in the early morning hours (from 7 a.m. to 8 a.m.) yield to a general shortening of the sell sojourn time (see Tab. 3.4) and therefore the shortening of cannel holding times.

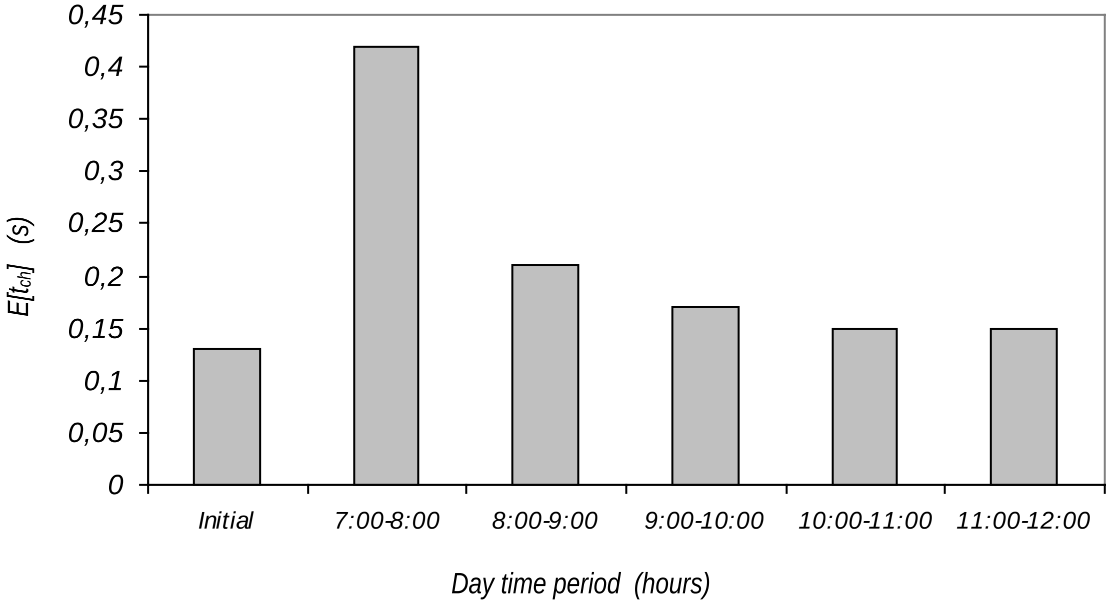

Figure 3.26 **:** Mean channel holding time for all calls.

Figure 3.27 illustrates the variation of the channel holding time with cell size. It can be shown that the cell size increases, the average channel holding time $E[t_{ch}]$ approaches the average call holding time $E[t_c]$.

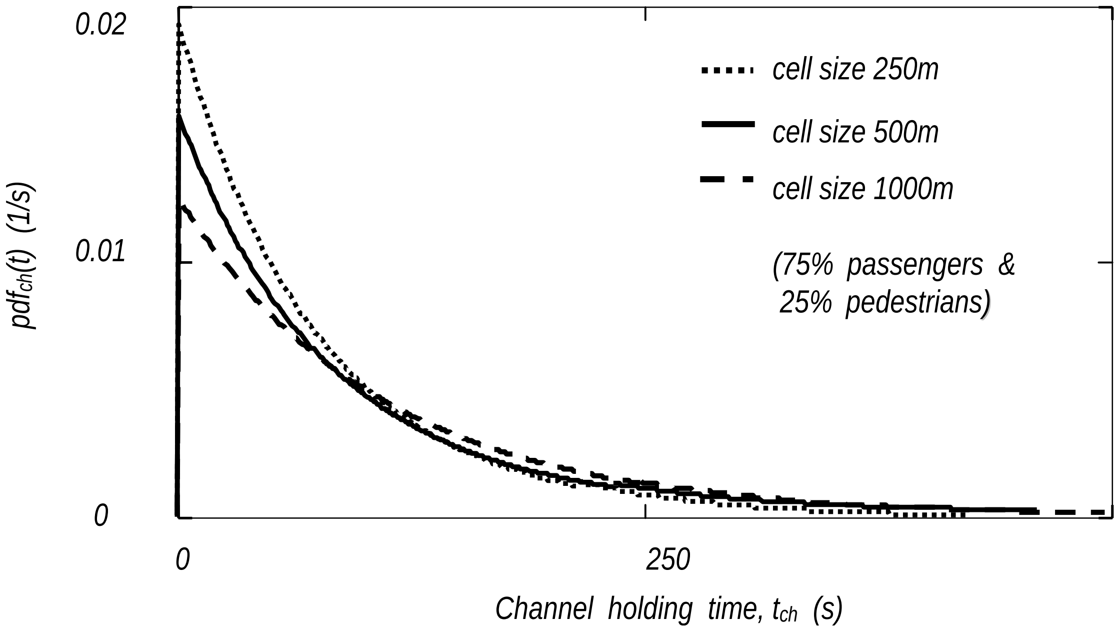

Figure 3.27 **:** Probability density function of channel holding time of the moving users for different cell sizes.

Part II

Evolution of Wireless Communication Networks

And the last, in every case to make enumeration's so complete, and reviews so general, that I might be assured that nothing was omitted.

René Descartes
(DISCOURS DE LA MÉTHODE POUR BIEN CONDUIRE SA RAISON, ET CHERCHER LA VÉRITÉ DANS LES SCIENCES, 1637 - Discourse on the Method for Rightly Conducting One's Reason and Searching for Truth in the Sciences)

Chapter 4

Radio Resource and Location Management Aspects

4.1 Introduction

As users, services, databases, and computers become increasingly mobile, so fades the are of the fixed network. Modern networks are becoming mobile networks which must accommodate a broad range of services with differing mobility characteristics. Consequently, there is an impetus to understand mobility and its effect on communication systems. As an aid to greater understanding, here is proposed a theoretical framework for the study of mobility tracking based on user location distributions. Using stochastic ordering and information theory, can enable quantitative comparison of various mobility management schemes as well as insight into the mobility tracking problem over a wide range of mobility characteristics. This general approach should aid both applications and future research.

Mobility management is the cornerstone of cellular philosophy. It allows the subscriber to make and receive calls at any location in a network, provided there is radio coverage and the subscriber demands a service which has been registered. The application of the mobility model derived on Chapter 2.3 of this work are numerous. The mobility model can be combined with a range constraints on the performance of the system in order to estimate design parameters. In this section are illustrated how this model can be integrated in the whole mobility management concept, and how can be used to measure the performance of cell selection approaches in a multitier wireless cellular system based on user mobility behavior.

To model the wireless communication networks in a realistic way, several observations are in order. First, due to the wide spectrum of integrated communication services (such as phone calls, information retrievals, etc.) carried jointly over a wireless communication network, the assumption of call holding times being exponentially distributed, made in the past for evaluating the behavior of classical wireless or wireline networks, may no longer be valid. This is conformed via field studies. Second, due to user mobility and the irregular geographical cell shapes, the cell sojourn times will also typically have a general distribution. Third, the channel occupancy time in a cell, i.e., the time the channel is occupied by a call in a cell (a new call, a handover call, regardless of the call being completed in the cell or moving out of the cell) is also not necessarily distributed exponentially, as generally assumed in the past.

Location areas are geographical regions where a mobile user is paged when receiving a call. When a mobile leaves its location area it generates a registration procedure. In order to minimize the signaling due to registration procedure, it is desirable to include high mobility zones within a single location area and to have location areas as large as possible [Rub97]. However, paging load in the cell is also a constraint [Ses92], [Rei92], [Pol95]. Therefore a careful location area design is necessary [Brá96]. There are several strategies to define location areas [Ros97]. A mobility model is an useful tool to assess a given design, finding the number of times a mobile leaves a location area initiating a call registration process. This problem is of the same form of the described handover analysis and it is not elaborated on further.

4.2 Call and Handover Admission Strategies

In a cellular mobile system, continuity of the communication link when a mobile moves from one service area to an another service area can be regarded as the most important service feature provided to the customer. Any interruption to the communication or any deterioration to the service quality has a great impact on the image of the service provider. To provide uninterrupted communication, the call has to be switched over to the appropriate base station, at the correct time. This process is known as "handover" or "handoff". Handover of a call may be required in three situations:

- When the received signal strength is faded due to a deep shadow; then if the received signal strength of the neighboring base station is good, handover can be used to stop the drop-out of the call.
- When the mobile reaches a cell boundary; then the call has to be permanently handed over.
- In systems based on rearrangement, to accommodate a new call or handover-call, by freeing a channel using a forced handover of an existing call to an another cell.

Handovers require additional processing time and they have to be implemented within a short period of time in order to minimize the service interruption. For this purpose, the mobile switching center, *MSC*, the mobile station, *MS*, and the related base station, *BS*, have to be coordinated in decision and execution processes of a handover. Because of this, handover is a critical design consideration in cellular mobile systems.

In a homogeneous system the number of handovers required for a particular call is directly proportional to the number of boundary crossings a mobile undergoes during the period of a call. Hence the handovers occur more frequently in microcellular systems than in conventional cellular systems due to smaller cell size. This means that potential improvement of handover performance in small-cell systems is extremely important.

The handover process is a complex process which needs the fulfillment of a combination of activities. It includes a request made based on the propagation conditions, a decision based on this request and the traffic situation, and the execution of this including switching. Further, these activities need considerable processing time. Figure 4.1 shows the major activities involved in a handover process. Depending on how these activities are implemented in a system, the handover-related issues can be categorized into two areas. The first are concerned with how these activities are distributed and coordinated among *MS*, *BS* and the *MSC*. They can be regarded as system architecture level issues.

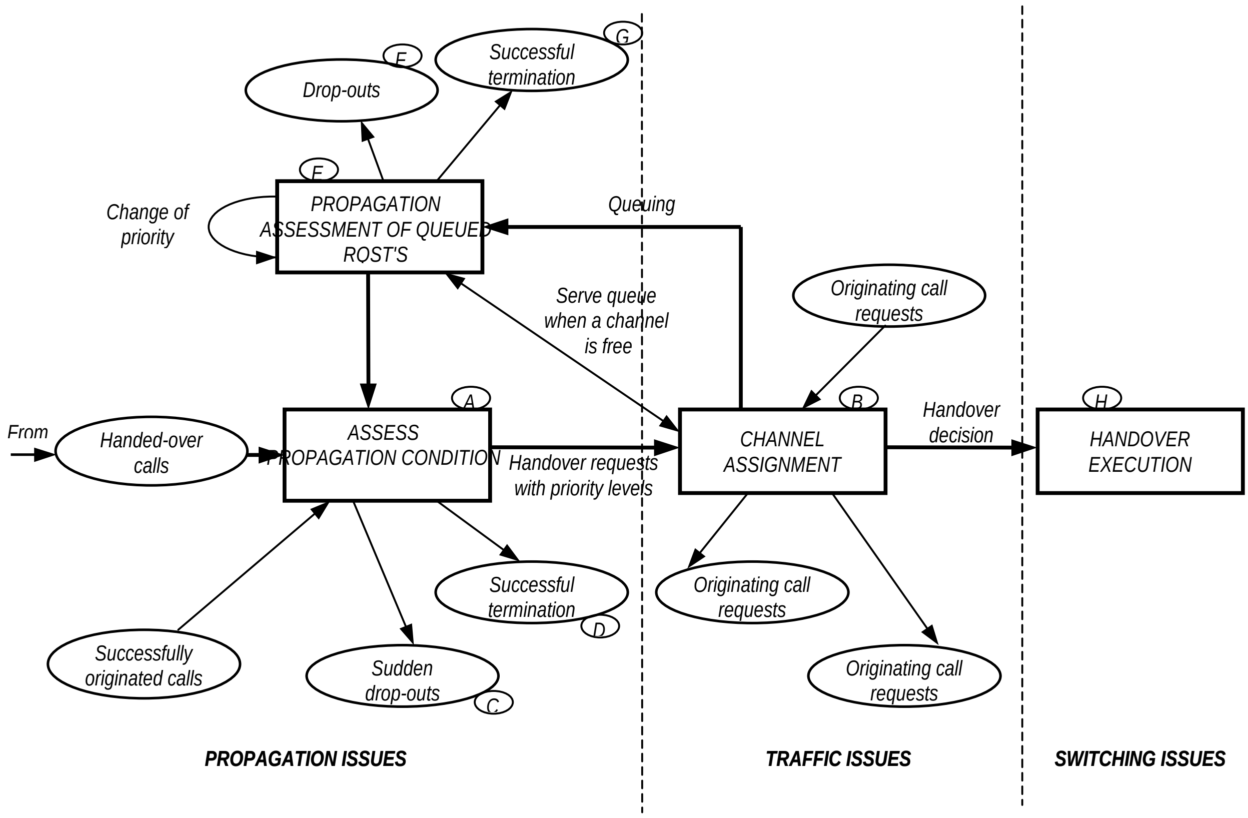

Figure 4.1 **:** Handover issues.

The second type of issues are concerned with how these activities are implemented and can be regarded as low level issues or process level issues. These low level issues are concerned with efficient algorithms for improving the various decisions involved in the handover process. In order to improve the handover performance a clear understanding of all the processes involved is essential. The process involved can be categorized as belonging to these three major areas, namely traffic, propagation, switching and processing. A handover can be successfully implemented if and only if: a neighboring base station having a sufficient signal strength is available, and the target base station has a free channel for communication; and the handover can be executed before any significant deterioration to the existing signal occurs.

The involvement of the different processes are illustrated in Fig. 4.1. These handover issues are described below.

Propagation Dependent Issues

The propagation assessment block *A* shown in Fig. 4.1 represents various measurements carried out by the *MS* and *BS*, and the prediction process based on these measurements to indicate the requirement of a handover to the channel allocation block *B*. However, the propagation requirement for a handover, mentioned above, cannot be met sometimes due to irregularities in cell coverage. This is due to the existence of areas which cannot be served by any of the *BT*s. If the hole is so large that the signal quality has been unsatisfactory and a target cell could not be found for more than some time limit (Drop-Timer), the call will be dropped out as indicated by the block *C* in the figure. This time limit defines the maximum bearable distributance allowed to a user by the system. Another possibility is that some calls can be successfully terminated without requiring any handover as shown by the block *D* in the figure.

Reliable Prediction Algorithms are very important for handover procedures. If the signal strength during the next measurement cycle can be accurately predicted using past measurements, the drop-outs can be minimized by taking decisions at the right place and time. Hence an accurate prediction process will improve handover performance, particularly for high speed mobiles.

Efficient Handover Strategies can minimize the number of handovers. We need to minimize the number of handovers as each handover increases the signal and processing load, and causes traffic management problems. This can be reduced by identifying necessary and unnecessary requests and trying to limit the unnecessary handovers. A handover can be considered unnecessary if the required quality can be sustained without that handover. Various methods of limiting unnecessary handovers include: usage of a hysteresis margin; usage of a long term prediction scheme when the signal strength is sufficiently high; or allowing a handover consistency timer to check whether the target cell remains as a favorable cell for specified time limit. These strategies are widely known as "handover strategies" in the literature and this is the major thrust of past investigations into handover performance [Sen94], [Vij93], [Lag96], [Rug96].

Traffic Dependent Issues

A call can also be dropped out due to non-availability of channels. The channel allocation block *B* in Fig. 4.1 illustrates how the new calls and the handovers compete for a channel. However, the drop-out of an existing call has more impact on the system performance from the point of view of the user than the blocking of a new call, and handover priority such as exclusive channel reservation for handovers and handover queuing schemes have been proposed to give handovers preference in channel assignment over new arrivals. In *exclusive channel reservation schemes*, some number of channels are exclusively reserved for handovers (see Fig. 3.1) so that the handover-blocking will be less compared to the new call-blocking. In a handover queuing system the handover will be queued whenever there is no channel available. This queue will be given priority whenever a channel is free.

This is shown by block *E* on Fig. 4.1. Blocks *F* and *G* show the possibilities of the drop-out of the call while in the queue due to expiry of the time-out period and that of the successful termination of the call while in the queue, respectively. This expiry is dependent on the propagation situation of the call and if the handover request was an urgent one where the propagation condition is very bad, then it is more likely that the call will be dropped-out soon. The above cannot be modeled accurately when considering the traffic situation only, as this phenomenon depends on the handover request algorithms as well. Another difficulty of modeling in a traffic environment is that of modeling handover requests, which are purely dependent on the mobility and propagation environment. Hence to be able to model realistically, both traffic and mobility conditions have to be considered. In [Hon93] analytical work has been done to investigate the performance and in [Ses92] a simulation study has been carried out.

As shown in Fig. 4.1, there are two other possibilities which can happen while waiting in the queue. One is the withdrawal of the handover request, if the signal strength improves again. The other possibility is that can change the priority allocated to it. This priority is decided according to the propagation environment. The change of propagation conditions its due to mobile movement. The assigned priority is used by the system's which employ handovers queues served according to the priority of the call. This priority to a handover-call at the time of handover request depending on the urgency of the situation.

Switching and Processing Issues

The criterion that a handover be completed before signal strength degrades unacceptably can be improved by employing efficient switches, frequency synthesizers for fast tuning, efficient coordination schemes between stations, efficient distribution of work load among the stations, and high speed processors to implement software algorithms at a reasonable speed.

We can summarize the above discussion by stating the key issues which needed to be addressed in order to improve handover performance. These issues belong to one of the three main areas discussed previously.

- Efficient coordination and decision making architectures which minimize handover switching and processing delay.
- Accurate prediction algorithms for signal strength and signal quality.
- Efficient handover request decisions based on propagation measurements.
- Efficient means of giving priority to handovers over new calls in channel assignment.
- Efficient priority level assignment schemes based on realistic mobility modeling and mobility behavior prediction.

Figure 4.2 illustrates the interrelationship of these five important issues. Obviously, there exists a great independence among these areas, and our target should be to find optimum parameter set for each of these algorithms for a given environment. Due to the intractability of the enormous number of combinations available with these five schemes, we try to analyze the schemes only in a combined/multilayer environment. While it is important to study the effect separately so that a relatively simpler system results for investigation, it is important to study their interdependency. To observe how they can be used in a practical environment.

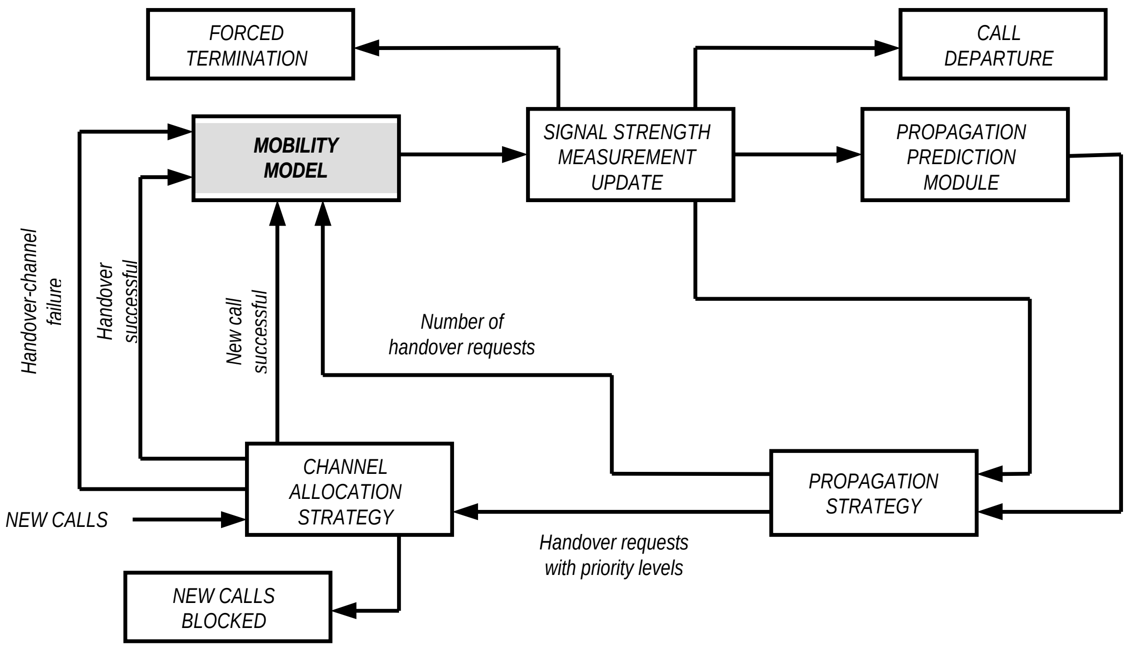

Figure 4.2 : Different decision procedures involved in handover process.

In a cellular wireless communications network, the network delay for a handover request is limited by a timeout period. If the network fails to respond within the timeout period, the handover call is forced terminated. In following, are studied the effect of the network response time on the performance (the call incompletion probability) of a mobile cellular system.

The capacity of a cellular system can be increased by reducing the coverage area of a cell. A decrease in the coverage area, however, is constrained by the requirement that a subscriber unit remains in the cell for a time interval sufficient enough to complete the call set up and all handover functions. Conversely, in order to achieve smaller cell sizes, it may be necessary to reduce the processing times for these functions. In either case, one needs to know the relationship between the cell size and call set up and handover processing times or, more generally, the call processing times.

Such a relationship is derived by computing the probability that a subscriber unit, initiating a call anywhere in the coverage area of the cell, will be covered by that cell for a time interval equal to the time it takes for call set up and handover combined. By fixing the cell size one can determine the coverage probability for a given call processing time T_{cp}, and vice versa. Table 4.1 compares the coverage probabilities of a cellular system that would meet specified call processing requirements for different cell sizes and shapes.

Table 4.1 **:** Coverage probability for hexagonal and sectorized cells with different sizes.

Call processing time, ***T_{cp} (s)***	***Coverage probability, Pr[t_{rs} > T_{cp}] (%)***			
	Hexagonal cell, r = 250m	*Sectorized cell, R = 662.5m*	*Hexagonal cell, r = 500m*	*Sectorized cell, R = 1325m*
5	*82.8*	*90.1*	*91.8*	*95.3*
10	*75.7*	*85.8*	*88.4*	*93*
15	*68.8*	*81.3*	*84.8*	*91*
20	*63.1*	*77.6*	*82.1*	*89.5*

Suppose that the call processing time is 5 seconds, and the cell range is 500 meters. Then the mobiles can be covered by this hexagonal cell with a 82.8 per cent probability or better. The cell capacity loss in this case is obtained by computing the probability

$$\mathrm{Pr}_{capacity\text{-}loss} = 1 - \mathrm{Pr}[t_{rs} > T_{cp}] = 17.2\ \% \quad . \tag{4.1}$$

4.3 Call and Handover Blocking Probabilities

The main aim of building a traffic simulation model (which include both the teletraffic and the mobility model) is to obtain the respective blocking probabilities, and for this purpose the length of time the network remains in a certain state is not of any significance. Therefore, the used traffic simulation model is based on the next-event time-advance approach which uses all attributes of the current and next calls. These attributes include call duration, call interarrival time, remaining sojourn time and handover sojourn time. A very large population of mobile users is assumed in each cell, so that the mean call arrival rate will be independent of the number of calls in progress. The call duration times are assumed to be independent and identically distributed random variables, which follow the negative exponential distribution. Remaining and handover sojourn time distributions follow the generalized gamma distribution according to the results of mobility modeling in Chapter 3.3. The cellular system is composed from hexagonal cells with a reuse cluster size of 7 cells. A handover occurs from a cell to each of the six neighboring cells with an equal probability of 1/6. The mobile user calling behavior is in according with assumptions in Chapter 3.2.

To obtain the performance parameters for the cellular network modeled in Figure 3.1 we consider the following. Traffic in a cell is divided into two classes served by a total of N_{ch} channels per cell but with preferential treatment for service in one class. The two classes consist of newly arriving traffic at the rate of λ_i having access to $N = N_{ch} - N_g \geq 0$ channels and handover traffic at the rate of λ_h with additional exclusive access to $N_g \geq 0$ (guard channels).

The new arriving traffic can be assumed as a Poisson process. Note that the handover traffic depends on he total traffic carried in a cell, and in a homogeneous case can be invoked the flow balance property (the incoming rate of handovers to the cell of concern is equal to the outgoing rate of handovers to adjacent cells). The handover traffic can be approximated by a Poisson process [Vij93], [Chl95]. This assumption allows to write the aggregate traffic process as Poisson. Assuming an exponential distribution of call duration in the cell (or channel holding time as defined in Chapter 3.5) can be obtained the steady state blocking and handover probabilities using a Markov chain model. When no queuing of new or handover calls is performed these probabilities are given by the following expressions:

$$\mathrm{Pr}_b = \frac{(\rho_i + \rho_h)^N \sum_{k=N}^{N_{ch}} \frac{\rho_h^{k-N}}{k!}}{\sum_{k=0}^{N-1} \frac{(\rho_i + \rho_h)^k}{k!} + (\rho_i + \rho_h)^N \sum_{k=N}^{N_{ch}} \frac{\rho_h^{k-N}}{k!}} \ , \tag{4.2}$$

$$\mathrm{Pr}_{hf} = \frac{(\rho_i + \rho_h)^N \frac{\rho_h^{N_g}}{N_{ch}!}}{\sum_{k=0}^{N-1} \frac{(\rho_i + \rho_h)^k}{k!} + (\rho_i + \rho_h)^N \sum_{k=N}^{N_{ch}} \frac{\rho_h^{k-N}}{k!}} \ , \tag{4.3}$$

with $\rho_i = \frac{\lambda_i}{\mu_c}$, and $\rho_h = \frac{\lambda_h}{\mu_c}$.

Solving the set of nonlinear equations above, one obtains the performance measures for probability of blocking and handover failure. In the case where $N_g = 0$, newly arriving and handover traffic are treated alike, and the two performance measure above are simplified to $\mathrm{Pr}_b = \mathrm{Pr}_{hf}$ given by the Erlang loss (Erlang B) formula. Figure 4.3 illustrates how new and handover call blocking probabilities (obtained by computer simulations) vary with the new call attempt rate per cell for various cell sizes (or mobility behaviors). This figure shows that with increasing cell radius, blocking probability approaches the Erlang-B distribution.

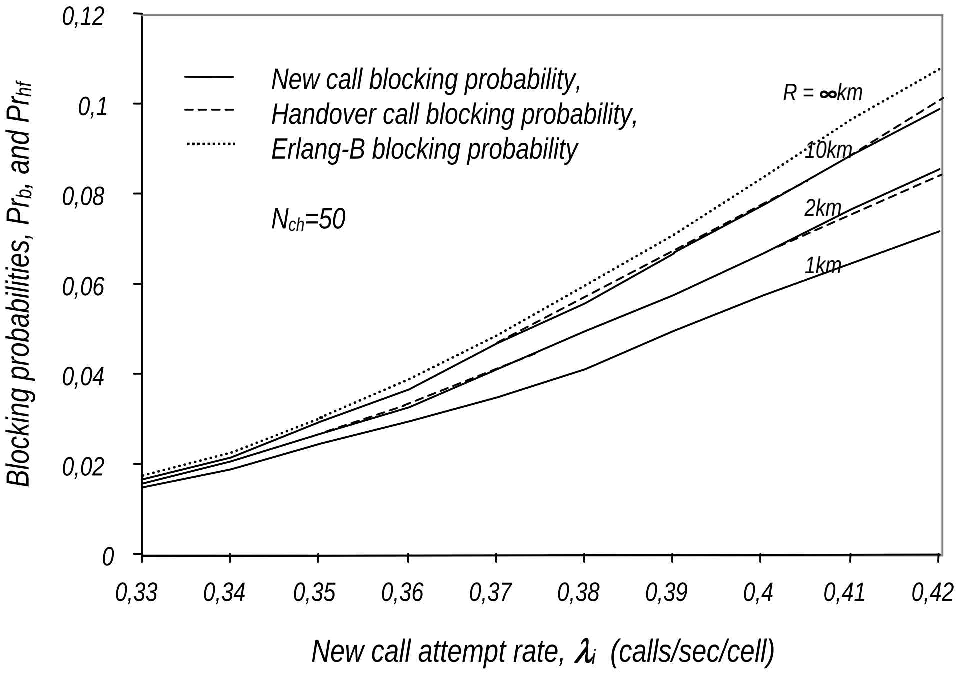

Figure 4.3 **:** Blocking probabilities for different sell sizes.

The same data is shown in Fig. 4.4, as a function of offered traffic considering effective call holding time. As it is illustrated in this figure, simulation results for blocking probability variation with respect to effective offered traffic per cell is independent of cell size as considered in [Tek94]. This means that for a given new call arrival rate, the effective channel holding time in a cell is such that consequent traffic intensity remains constant.

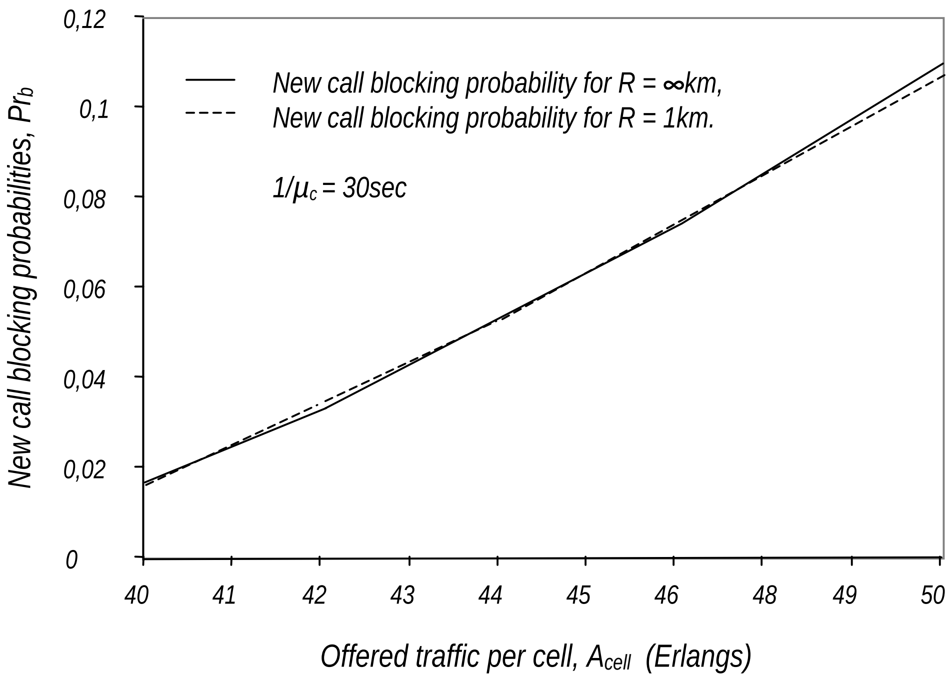

Figure 4.4 **:** New call blocking probability versus different offered traffic.

4.3 Call Dropping Probability

The probability that a call will be dropped out during a call is another measure of traffic performance. The dropout probability, $\Pr_d$, is defined as the probability that a call will be dropped out at any point during a call, while the handover blocking probability is simply the same measure per cell boundary crossing. A fraction of the new calls which is not blocked will eventually be forced into termination if it succeeds in each of the first (*i* -1) handover attempts, but fails on the i^{-th} handover attempt. For a call in progress the probability of call dropping can easily be determined as follows [Hon86]:

$$\begin{aligned} \Pr_d &= \Pr_h \Pr_{hf}[1+\Pr_h(1-\Pr_{hf})+\Pr_h{}^2(1-\Pr_{hf})^2+...] \\ &= \Pr_h \Pr_{hf} \sum_{i=0}^{\infty} \Pr_h{}^i (1-\Pr_{hf})^i \end{aligned} \tag{4.4}$$

or

$$\Pr_d = \frac{\Pr_h \Pr_{hf}}{[1-\Pr_h(1-\Pr_{hf})]} \; . \tag{4.5}$$

Figure 4.5 shows how the dropout probability decreases with the increasing cell size.

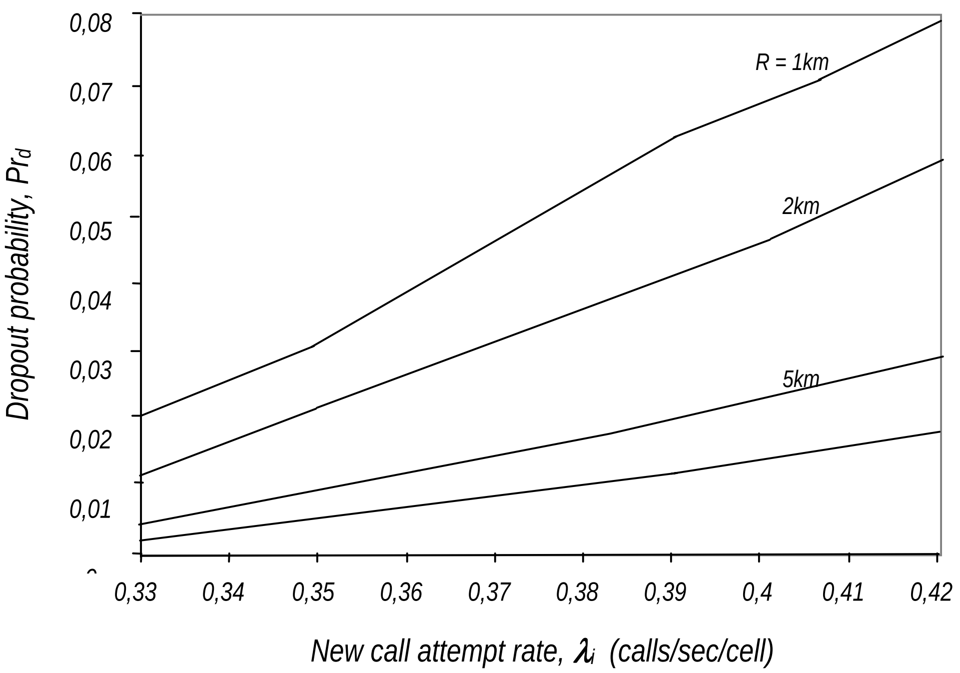

Figure 4.5 **:** Dropout probability for different sell sizes.

Figure 4.6 shows the dropout probability versus handover call blocking probability.

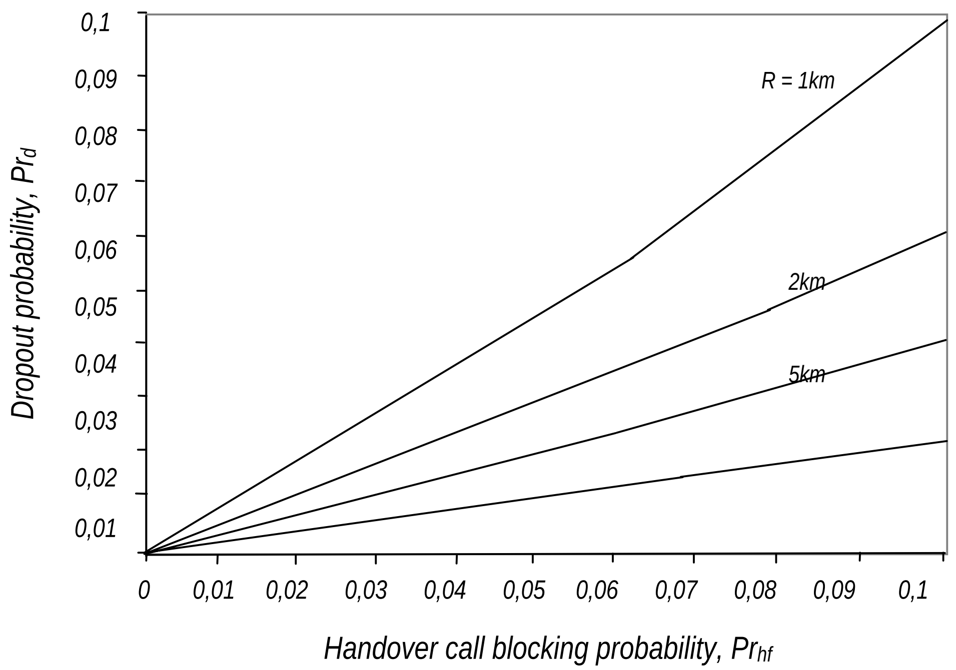

Figure 4.6 **:** Dropout probability versus handover call blocking probability.

It should be noted that two networks with the same handover probability could have different dropout probabilities. For example, a network with slow moving users will experience a relatively lower number of boundary crossing attempts than a network with fast moving users. The greater the number of boundary crossings produced, the greater will be the dropout probability for the same handover blocking probability. Dropout probability depends on the cell size, the new call attempt rate and the mobility behavior of users.

The model depicted in Fig. 3.1 can be considered for the case when all calls are queued. A number of current networks queue both calls. Queuing of incoming calls may result in reduced load on switching and signaling processors.

4.5 On the Optimal Design of Multilayer Wireless Systems

The concept of *hierarchical* or *multilayer* (also called *multitier*) cellular systems (Fig. 4.7) appears to be a logical extension of the cellular system. Hot spots are covered by microcells (layer 1) while the macrocells provide a continuous coverage of the service area (layer 2). In very dense areas a continuous coverage with both microcells and macrocells may be achieved. The mobility and teletraffic aspects of wireless networks are critical to understanding the problems of and contrast between different architectures and strategies.

Propagation conditions in microcells are highly dependent on the environment [Löw92]: width of the street, moving obstacles, and so on. Users may experience a dramatic decrease of the signal strength when they turn a street corner. Such rapid variations of the received level may cause communication interruptions for high-speed terminals because the network does not have enough time to hand over the communication when the terminal leaves a cell. Furthermore, such high-speed terminals may generate a lot of handover and hence cause a signaling increase in the network [Pol95], [Bra96].

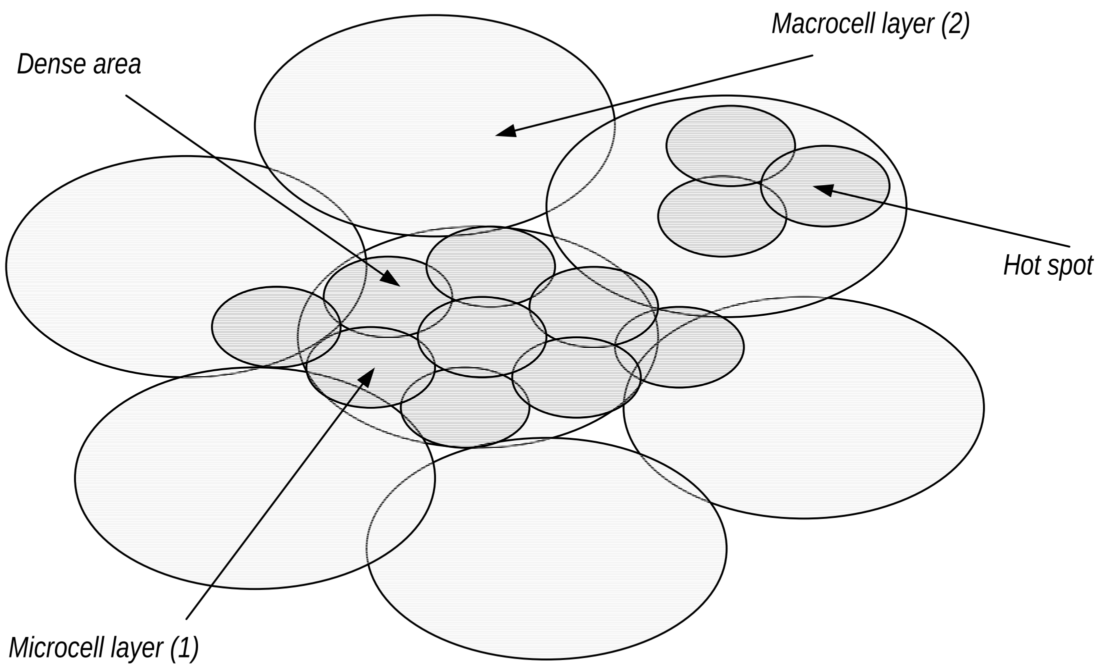

***Figure 4.7* :** Multitier cellular system.

Once the frequencies are allocated on micro and macro layers, terminals may be served by two cells in large areas. The question that rises is to known which policy provides the best efficiency.

Reversible and Nonreversible Hierarchical Systems

Two mobility behaviors may be easily separated in personal communications networks: pedestrians (especially in indoor environments) are quasi-fixed while users in their car or public transportation move quickly. The admission strategies must be optimized in areas where both layers are deployed.

Macrocells must accommodate high-speed terminals while microcells are more adapted for low-speed terminals. In order to maximize the system efficiency, all low-mobility users have to use preferably the lowest layer (i.e., microcell). Upper layers are used for high-mobility terminals and act as overflow recipients for low layers. In the so-called *nonreversible system*, a call is never taken back by the lower layer. In the *reversible systems*, the call may be taken back by the microcell layer as soon as resource is available (Fig. 4.8).

When a user sets up a call, the system does not generally known its speeds. It is always possible to direct the call toward the correct layer. The system may set up all calls on the microcell layer. Strategies to sort terminals based on the dwell time of mobiles in cell before the handover are proposed.

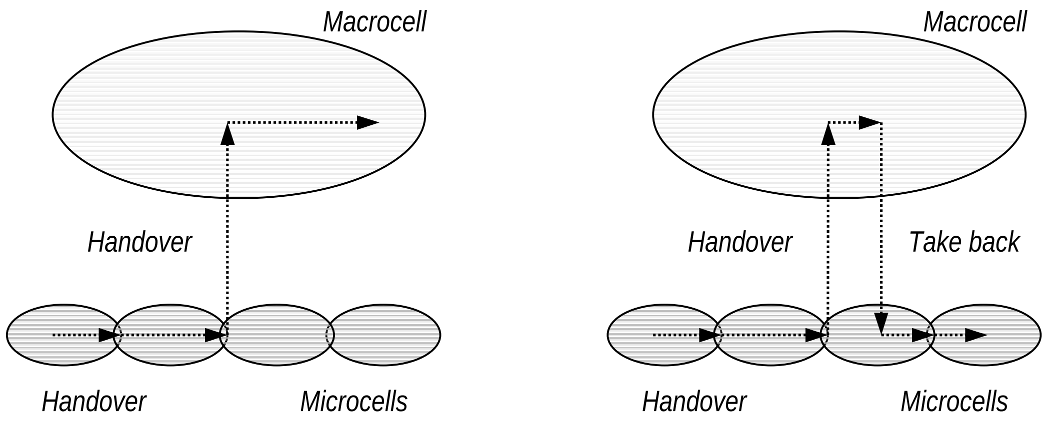

Figure 4.8 **:** Reversible and nonreversible systems.

Several teletraffic analyses are made for cell selection based on dwell time [Jan97], [Lag96], [Ben95], [Sun94]. In all studies, classical teletraffic assumptions are made: the cell sojourn time and the call holding time are exponentially distributed, the new call arrival rate is modeled as a Poisson process and new calls are always first placed in the lowest layer (microcells). When a given mobile needs to be handed over, if the observed sojourn time is lower than threshold t_{tr} or if there are no channels available on the same layer cell, the call is transferred to the upper layer. The lower threshold t_{tr} is, the higher the number of channels in macrocells must be. A small value of t_{tr} allows the signaling to be reduced for fast mobiles (mean number of handover) but with a dramatic increase in spent resources.

In classical systems, the handover is generally activated when the power budget on the neighboring cell is better than the current cell plus an additional margin *ho_margin*. In [Iva95], a mobile speed-sensitive handover algorithm is proposed for the *GSM* system. The margin depends on the cell sojourn time:

$$\begin{aligned} &\textbf{\textit{if}}\ \ t < DWELL\_TIME\ \ \textbf{\textit{then}}\ \ HO\_MARGIN\_TIME(t) = HO\_MAARGIN\_TIME + SO, \\ &\textbf{\textit{else}}\ \ HO\_MARGIN\_TIME(t) = HO\_MARGIN + SO - DO, \end{aligned} \tag{4.6}$$

where *SO* (Static Offset) is a static hysteresis to avoid the ping-pong effect between two neighboring *BS*s. Parameter *t* is a timer that is set when the neighboring cell becomes an acceptable candidate cell. In the first *DWELL_TIME* seconds, the new cell is put at a disadvantage by the value *SO*. This disadvantage is then reduced by the value *DO* (Dynamic Offset). For a low-speed mobile, after *DWELL_TIME* the neighboring cell is still received with a high level and hence the handover is made. On the opposite, a high-speed terminal will leave the coverage of the neighboring cell if it is a microcell before *DWELL_TIME*. Hence, macro-to-micro and micro-to-micro handovers are not made for high-speed terminals. It is shown that such an algorithm considerably reduces the number of unnecessary handovers from macro to microcells.

In *GSM*, the selection of the serving base station may be dependent on the speed of the terminal. The so-called *C2* criteria was introduced in the phase 2 *GSM* specifications [GSM05]:

$$\textbf{If } t < PENALTY\_TIME \textbf{ then } C2 = C1 + CELL\_RESELECT\_OFFSET - TEMPORARY\_OFFSET,$$
$$\textbf{else } C2 = C1 + CELL\_RESELECT\_OFFSET, \tag{4.7}$$

where *C1* is the margin on the minimum required path loss between the *BS* and the *MS*, *CELL_RESELECT_OFFSET* is an hysteresis to avoid the ping-pong effect between two neighboring *BS*s. The cell with highest *C2* value is selected. Parameter *t* is a timer that is set when the *MS* is entering a new cell. In the first *PENALTY_TIME* seconds, the new cell is put at a disadvantage by the value *TEMPORARY_OFFSET*. If a high-speed mobile enters a microcell and if the sojourn time is lower than *PENALTY_TIME*, the mobile will never select this microcell and will stay on the overlaying macrocell.

All previous sorting strategies analyze the sojourn time during a communication. Decisions are taken ***a posteriori*** and calls do not start on the best layer. It is possible to have the terminals ***a priori*** camped on the appropriate layer by improved cell selection processes on the basis of the mobility behavior prediction

The base station subsystem (*BSS*) tracks the user mobility by collecting yours past microcell sojourn times. The *BSS* estimates the mean sojourn time and compares it with a threshold for the microcell-macrocell selection. This procedure provides low probabilities of erroneous assignment. The threshold must be chosen so that it minimizes the handover processing load on the system while meeting the required blocking constraints. Furthermore it may be dynamically adapted to fit the varying traffic conditions.

In a two-layer hierarchical cell system, the basic mobility behavior prediction algorithm works as follows. Whenever a mobile is ready for a possible handover at the boundary of its present microcell, it decides independently with probability $\Pr[\mu \rightarrow M] \in [0,1]$ (μ stands for microcell, *M* for macrocell, respectively) to be assigned to the covering umbrella macrocell, or with probability $1-\Pr[\mu \rightarrow M]$ to the next microcell. $\Pr[\mu \rightarrow M]$ depends on a lot of parameters as are described in the following.

Given an accurate micro-macro cell selection procedure, the next problem of interest is the choice of mobility threshold. In following, we focus on the determination of the optimal mobility threshold value t_{tr} , which is a threshold on the mean microcell sojourn time. It is convenient to think in terms of a threshold speed v_{tr} such that calls from mobiles with speed $v < v_{tr}$ will be assigned to microcells; other calls will be assigned to macrocells. The velocity threshold v_{tr} is related to the mobility threshold t_{tr} through the mean microcell size. We will derive a relationship between the threshold v_{tr} and the traffic conditions and load in the system. When traffic load is light, it is possible to provide better quality of service by reducing v_{tr} so that more mobiles are assigned to macrocells and undergo fewer handovers. Fewer handovers fewer handover failures and interruptions. When the traffic load increases, the value of v_{tr} is increased so that more mobiles are assigned to microcells and more teletraffic can be carried. This dynamic adjustment of threshold must be performed by the network.

The threshold t_{tr} is a network controlled parameter and may be broadcast by the system. Mobiles may then originate on the microcell or macrocell based on a comparison on their mean microcell sojourn time with the broadcast value of the parameter t_{tr} . Alternately, the mobile may always send its origination request to the macrocell along with its mobility estimate. The network then uses the mobility estimate, along with system load to determine whether to assign a macrocell or a microcell channel. Since this mobility estimate can be tracked during the call, changes in mobility are reflected by having a microcell-macrocell "hand up" or a macrocell-microcell "hand down".

We further assume the following system constraints on the maximum value of v_{tr} :

- *Call Setup and Handover Delay*: Calls generated by mobile units with speeds greater than $v_{tr,su}$ must not be assigned to microcells. This is because the time the mobile spends in the microcell coverage area is insufficient to allow for completion of call set-up and handover functions (see Chapter 4.2).
- *Handover Process Capacity*: The maximum number of handovers per second that can be processed by a microcell must be less than $\lambda_{h,max}$. For a given velocity distribution and total call arrival rate, this limits v_{tr} to be smaller than a corresponding velocity threshold $v_{tr,ho}$.

Let the new call blocking probability requirement at both macrocells and microcells be $\Pr_b$. Let $\Pr_{b,macro}$ and $\Pr_{b,micro}$ be the call blocking probability in macrocell and microcell, respectively. When the traffic load is light, $\Pr_{b,macro}$ and $\Pr_{b,micro}$ are below $\Pr_b$. Assume $pdf(v)$ the velocity distribution of mobile users in a system remains unchanged when the teletraffic load increases. Let A_{in} be the initial teletraffic load to a macrocell and its embedded microcells. Whenever possible, let v_{tr} be set such that the traffic partitioned into the macrocell and microcells makes $\Pr_{b,macro} = \Pr_b$ and $\Pr_{b,micro} < \Pr_b$. When v_{tr} is increased, $\Pr_{b,macro}$ will decrease and $\Pr_{b,micro}$ will increase. v_{tr} can be increased up to a point such that either $\Pr_{b,macro} = \Pr_b$ or $v_{tr} = \min[v_{tr,su} , v_{tr,ho}] = v_{tr,su}$, whichever occurs first. v_{tr} can assume any values within this range since the blocking probabilities at both macrocell and microcell satisfy the grade of service requirement $\Pr_b$. Furthermore, assume the number of channels in each microcell and macrocell is ten and no channel is reserved for handovers. Let the blocking probability requirement

The proposed multilayer was implemented by a computer simulation. The parameters used for the simulation are: $w_{-90°} = 0.75$, $w_{90°} = 0.5$, $w_{180°} = 0.0625$, $\sigma_\varphi = 0.125\pi$; $\bar{d}$ =100m, σ_d = 100m, Rice-distributed; w_{mr} =0.5, $\bar{v}$ = 10km/h, $\bar{v}_{mr}$ = 35km/h, σ_v = 10km/h. Figure 4.9 shows the computed optimal values of v_{tr} versus different offered teletraffic loads, A in Erlangs. For A < 5.1 Erl, all calls can be carried by channels in macrocell and the call blocking probability $\Pr_{b,macro} \leq \Pr_b = 0.02$. The optimal value of v_{tr} such that the handover rate λ_h is minimized is $v_{tr} = 0$.

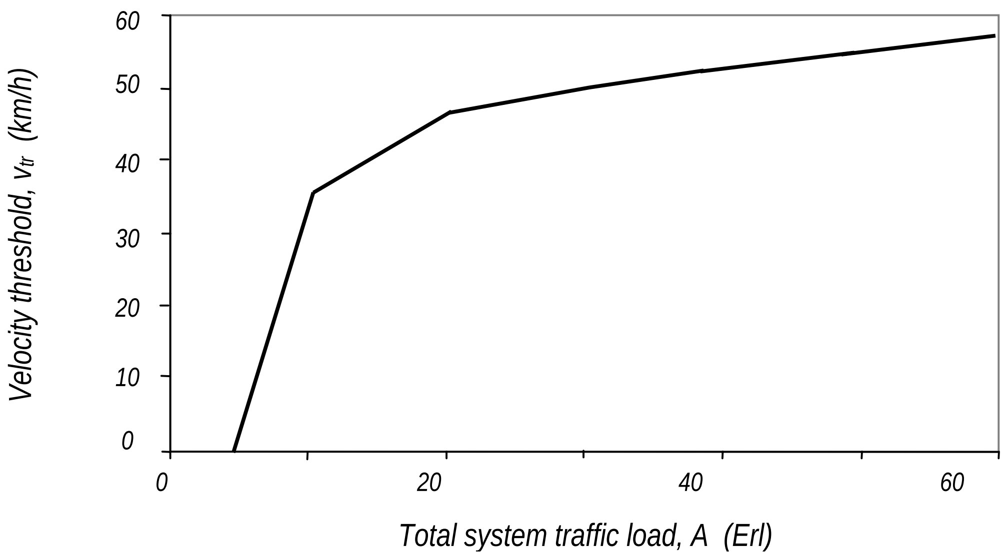

***Figure 4.9* :** Velocity threshold determination.

4.6 Forecasting Traffic

In [Bal98] a network based approach for the characterization of mobile velocity in *GSM* is investigated, using signal strength measurement reports of mobile terminals in active mode. The simulation results are very encouraging and suggest that the proposed neural network is capable of estimating whether a mobile user is moving slowly or quickly. However the proposed method is computationally lavish and yields consistent results only for a small part of mobile users.

Concerning this issue, various approaches can be found in the literature. In particular, the effect of user mobility on the traffic volume is considered insignificant. Traffic volume estimations is based on simple mobility models, assuming also simple cell shapes.

4.7 Toward an *SDMA*-Systems Analysis

Recently, an rapidly expanding research area in mobile communications is Space Division Multiple Access (*SDMA*) [Tan94], [Bon98]. Adding a further multiple access component to existing multiple access systems, *SDMA* is a promising technique for enhancing system capacity. To thoroughly evaluate the effects of *SDMA* on system capacity, however, a thorough understanding of the following factors interact is necessary: the spatially selective channel [Fuh98], the signal processing algorithms (e.g., beam forming, direction finding and tracking), equalization and coding [Gra98], user mobility and calling behavior. One particular problem is, that the state of the *SDMA* radio channel, i.e. propagation conditions etc., strongly depends on the user's location and mobility, as well as it depends on the environmental conditions. Interference between neighboring beams depends on the quality of the beamforming and tracking algorithms as well as the user's position and movement. To summarize, when taking into account not only simple systems with equally distributed user locations but also more realistic systems with inhomogenities of mobility terminal positions and call origination's as well as user mobility, dramatic drops in the additional capacity gained by *SDMA* can be expected. Therefore, for a proper analysis of *SDMA*-induced capacity gains, it is necessary to take an integrated modeling approach for the user behavior.

The spatial user distribution has to be modeled as it changes with time. Thus, two processes can be distinguished. First, an initial position for a new user has to be chosen randomly according to some spatial distribution. After initialization, the user position has to be changed with time according to the mobility model. The mobility model determines rules for the transition of the mobile user from position $[X(t), Y(t)]$ at time t to position $[X(t+\Delta t), Y(t+\Delta t)]$ at time $t+\Delta t$.

To get a first impression of the effects of mobility, simulations have been conducted, using the in Chapter 2.3 described mobility model to obtain information on how a mobile user's angle ψ with respect to the base station (*BS*) and the distance R between mobile station (*MS*) and *BS* changes with time, Fig. 4.10. Both ψ and R are important parameters for the intracell channel assignment and for the beamforming. Their variation during ongoing calls necessitates tracking procedures to set in well adjustment the radiated power and eventually leads to intracell handovers when users ate no longer spatially separable, e.g. when beam collisions occur.

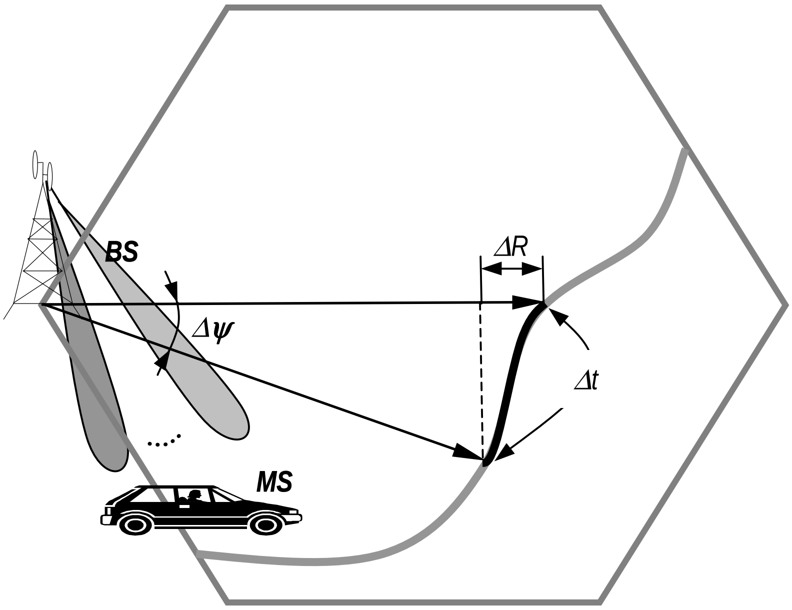

Figure 4.10 **:** A mobile terminal route. Relative angle and distance variation.

The relevant mobility modeling for a *SDMA*-system follows the well known trace routing as shown in Fig. 4.11.

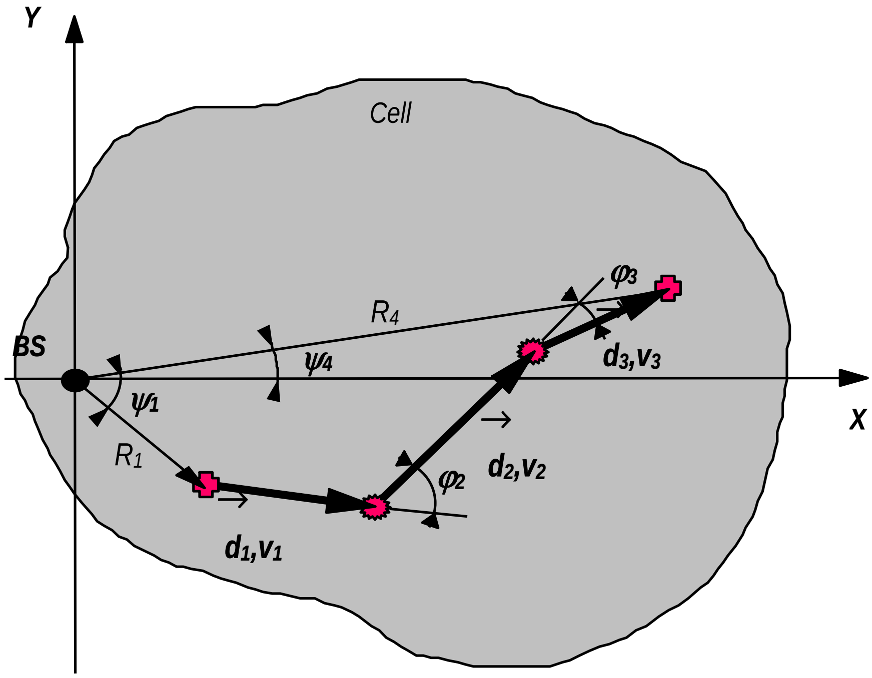

Figure 4.11 **:** Tracing a mobile terminal within the cell. Absolute angle and distance variation.

A single hexagonal cell with a diameter $2r$ =1000m is simulated. The basis station is positioned in accordance with Fig. 4.10 at cell border. A city center scenario with 50% pedestrians and 50% passengers penetration rates is chosen. The mobility model parameter values have been set as follows: ***a***) for pedestrians: $w_{-90°}$ = 0.5, $w_{90°}$ = 0.5, $w_{180°}$ = 0.125, $\boldsymbol{\sigma_{\varphi}}$ = 0.25π; $\bar{d}$ = 50m, $\boldsymbol{\sigma_d}$ = 40m, Rayleigh-distributed; w_{mr} =0, $\bar{v}$ = 4.6km/h, $\bar{v}_{mr}$ = 0km/h, $\boldsymbol{\sigma_v}$ = 3.7km/h; and ***b***) for passengers: $w_{-90°}$ = 0.75, $w_{90°}$ = 0.5, $w_{180°}$ = 0.0625, $\boldsymbol{\sigma_{\varphi}}$ = 0.125π; $\bar{d}$ =100m, $\boldsymbol{\sigma_d}$ = 100m, Rice-distributed; w_{mr} =1.25, $\bar{v}$ = 10km/h, $\bar{v}_{mr}$ = 45km/h, $\boldsymbol{\sigma_v}$ = 10km/h.

Figure 4.12 shows the plot of a histogram for the value of relative angle variations $\Delta\boldsymbol{\psi}$ that occurred during one second of movement.

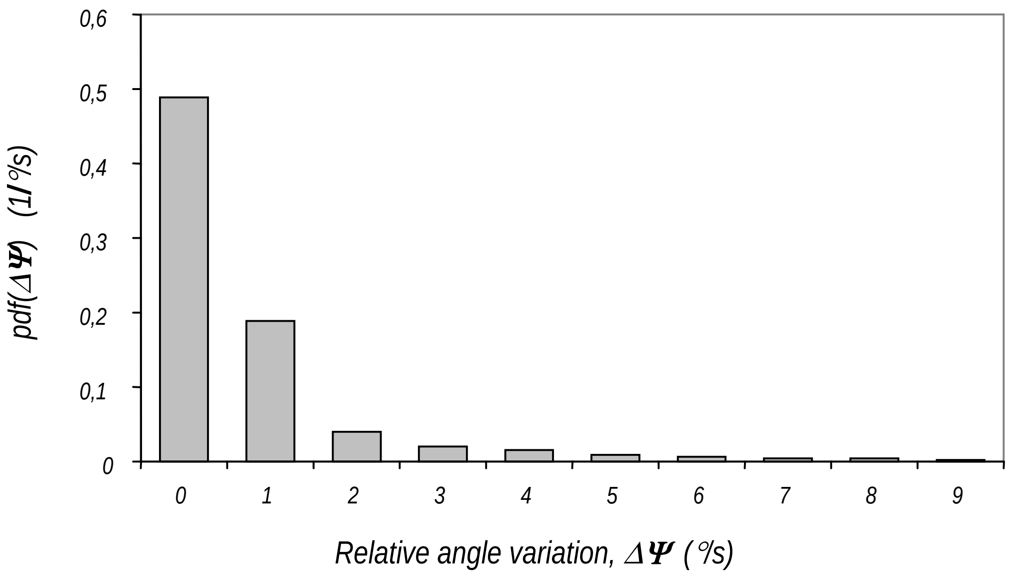

Figure 4.12 **:** Histogram of relative angle variation per second.

The second parameter, which are concerned with besides the angular position of the *MS*, is the distance between *MS* and *BS*. Figure 4.13 shows the probability distribution function of distance variation, ΔR , for time period of one second.

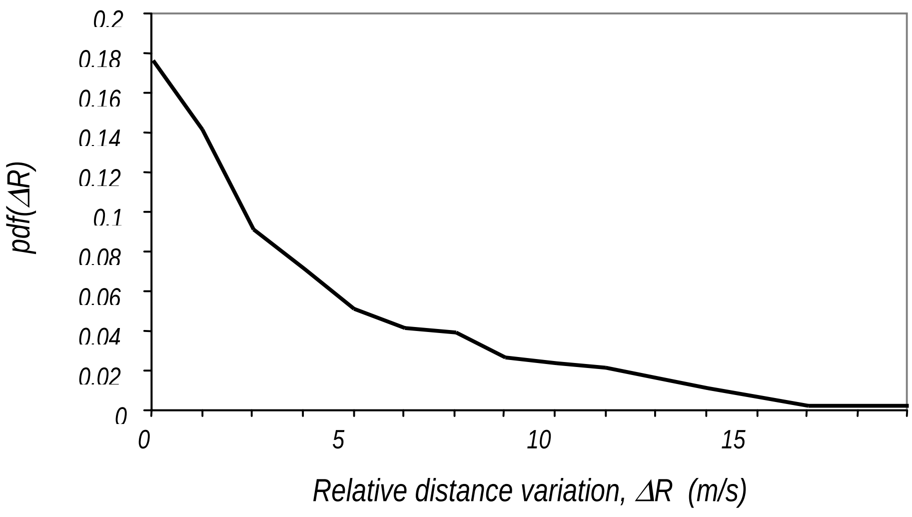

Figure 4.13 **:** Probability distribution function of distance variation per second.

Table 4.2 presents the mean values of relative angle and distance variation for time periods of 1, 10 and 60 seconds, respectively.

Table 4.2 **:** Mean values of relative angle and distance variation.

	Δt=1s	Δt=10s	Δt=60s
$E[\Delta \Psi]$	1.5 °/1s	15 °/10s	36 °/60s
$E[\Delta R]$	3 m/1s	34 m/10s	156 m/60s

The results indicate that, depending on the scenario, the parameters ψ and R of a user can change heavily during an average call duration. From this it can be concluded that user mobility will cause channel rearrangements and thus intracell handovers. However, work has still to be done to translate angular and distance variations into actual handover rates, since this depends on a range of such as e.g. the radio channel, the beamforming algorithm and the channel assignment procedures.

Conclusion

In this work, have been proposed a mobility modeling approach which caters for the whole range of design aspects met in third-generation mobile telecommunications systems (e.g., location and paging area planning, handover strategies, cell layout, channel assignment schemes, etc.).

The analytical defined mobility model presented in this work incorporates all the above mentioned features. The core of the model focuses on the estimation of the time it takes a busy mobile user to leave a cell area and the cell border crossing rate. This allows for the estimation of the handover rate and the channel holding time within a cell. The major advantages of the model are: *a*) the simple closed form solutions, *b*) its independence from the applied radio resource management scheme, and *c*) its accuracy. The latter has been validated via a simulation tool which accommodates different cell-layout scenarios over a geographical area which represents a "typical" city environment.

Mobility modeling in cellular mobile systems has to deal with the effect of the user mobility on the traffic volume per cell: A mobile user during an ongoing call may move from a cell area to an adjacent one, thus invoking the handover procedure. During this procedure, radio resources of the originating cell are released while radio resources of the target cell are assigned to the call. From the traffic viewpoint, user mobility results in: *a*) reduction of the resource occupation time compared to the total call duration (regarding a single cell), *b*) the radio resources of a cell should cater for both new call and incoming handover requests, and *c*) abnormal call termination due to lack of resources in the target cell (call dropping).

In the outdoor environment, users move using various transportation media (e.g., pedestrians, car, public transportation, etc.). This fact affects mainly the average time a user spends inside the cell area and consequently the rate of handovers. The mobility model jointly with a traffic model provides simple analytical results regarding the traffic streams characteristics and provides means to estimate the following parameters:

- offered telecommunication traffic volume,
- carried telecommunication traffic volume,
- call blocking probability (i.e., the probability a call is blocked during the set-up phase),
- handover blocking probability (i.e., the probability a handover request is rejected due to lack of resources),
- call dropping probability (i.e., the probability an active call is terminated during a handover),
- handover rate, and
- average number of handovers per call.

All the above listed parameters are expressed as a function of the user calling and mobility behavior. To assess the accuracy of the proposed mobility model a simulation tool has been constructed. The tool takes into account the user traffic and mobility behavior over different environments (high density city center, outskirts). Simulation trials, measurements, and theoretical results coincide, indicating thus the excellent accuracy the analytical described mobility model provides.

The material in this work was organized as follows. First defines the traffic model by determining: *a*) the environments that can be met in cellular mobile systems, *b*) the mobility related assumptions from the traffic viewpoint and *c*) the traffic streams that the offered traffic is composed of. In Chapter 3, the user sojourn time, the average number of handovers per call, the arrival rate of handovers and channel holding time is estimated, while Chapter 4 presents an iterative approach which leads to the estimation of the call and blocking probabilities. The call dropping probability is estimated respectively.

Future Work

The mobility model devised in this dissertation can be extended to model more accurately the system design parameters in time across the whole cellular coverage area. The characterization of spatial and temporal behavior of traffic can be achieved based on the model.

Some options for further research, besides the development of more realistic, better measurement based and environment dependent issues of the proposed mobility model, could include the following:

More detailed study how the user motion influences the call duration and the call arriving rate.

Improved teletraffic models are needed for mobile networks, in which resource demand varies with time, geography, and the environment.

Another aspect for future work is better to model time-varying behavior, which allows investigation into transient, peak, and average performance.

Using the proposed framework, a lot of large-scale simulations can be performed. They are useful in areas such as network architecture comparisons, network resource allocations, and performance evaluations of protocols.

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Appendix A

Generalized Gamma Distribution

An random variable t has a generalized gamma distribution if

$$pdf(t;a,b,c) = \frac{c}{b^{ac}\Gamma(a)} t^{ac-1} e^{-(\frac{t}{b})^c}, \qquad t > 0 . \qquad \text{(A.1)}$$

In the above, a, b and c are positive numbers and

$$\Gamma(a) = \int_0^\infty x^{a-1} e^{-x} dx \ , \qquad a>0,\ a \in R. \qquad \text{(A.2)}$$

is the gamma function. This function is also called the generalized factorial because $\Gamma(a+1)=a\Gamma(a)$.

Substituting different values for a, b, c produces various well known distributions as per (A.3), which usually have applications in determining the time to complete a task (Fig. A.1):

$pdf(t;1,b,1)$	Exponential distribution,
$pdf(t;a,b,1)$	Gamma distribution,
$pdf(t;1,b,c)$	Weibull distribution,
$pdf(t;\frac{n}{2},2,1)$	Chi-square distribution (n = degree of freedom),
$pdf(t;1,x\sqrt{2},2)$	Rayleigh distribution (x > 0),
$pdf(t;K,\frac{1}{\mu},1)$	Erlang distribution (K = integer value, μ > 0).

(A.3)

The special case $pdf(t;1,b=\frac{1}{\rho},1)$ gives the negative exponential distribution

$$pdf(t;\rho) = \rho . e^{-\rho . t} \ , \qquad t > 0 \qquad \text{(A.4)}$$

which is the classical waiting-time to an event of uniform probability density.

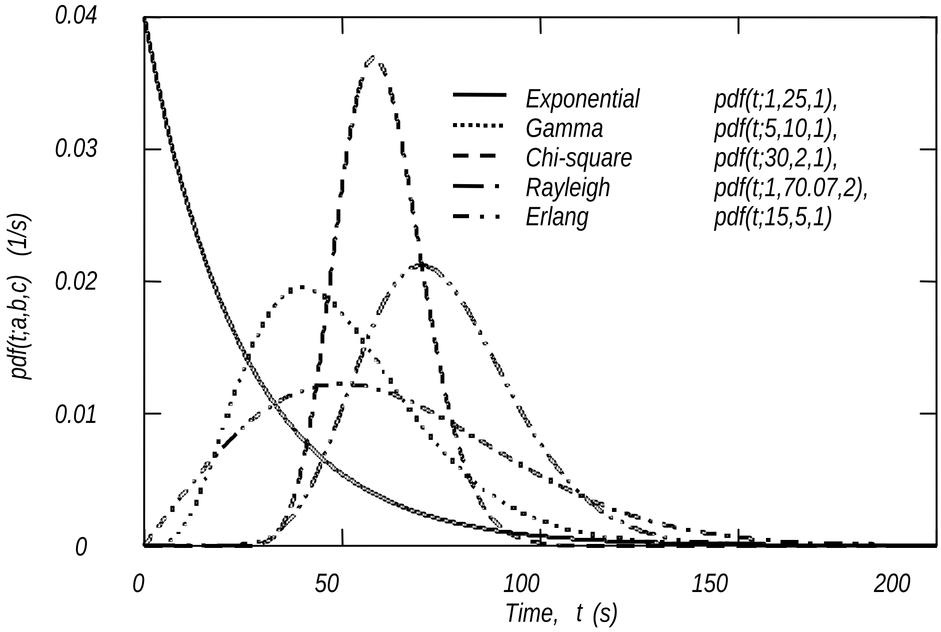

Figure A.1 : Examples of generalized gamma density function.

Finally, the special case $pdf(t;a,b,1)$ gives the gamma distribution with the density function

$$pdf_{\Gamma}(t) = pdf(t;a,b,1) = \frac{1}{b^a \Gamma(a)} t^{a-1} e^{-\frac{t}{b}} , \qquad t > 0 \qquad \text{(A.5)}$$

where a is called the shape parameter, and b is called the scale parameter. The mean and variance of this distribution are ab and ab^2 , respectively. Its Laplace transform is

$$L[pdf_{\Gamma}(t)] = PDF_{\Gamma}(s) = \left(\frac{\frac{1}{b}}{s + \frac{1}{b}} \right)^a , \qquad s > 0 \ . \qquad \text{(A.6)}$$

Appendix B

Chi-Square Goodness-of-Fit Test

The testing of distribution assumptions was done by applying the Chi-Square goodness-of-fit test. To accomplish this task, the following steps have to be performed:

Step 1: Sort data by data item values. This lets us visually see the data distribution as a histogram.

Step 2: Choose a distribution to which the data will be fitted and calculate the maximum likelihood estimation equations for the distribution's parameters.

Step 3: Create bins into which the data will be divided and find the expected number of observations in each bin. Bins should be created in a way such that the expected number of observations in each bin is equal according to the distribution being tested. This means that the bins have to be recalculated every time a different set of distribution parameters or a new distribution is being tested. The bin boundaries were chosen to satisfy

$$\Pr_i = \Pr[x < x_{(i)}] - \Pr[x < x_{(i-1)}] = \frac{10}{n}, \qquad i = 1, 2, ..., k, \qquad \text{(B.1)}$$

where

$\Pr_i$ is the probability of a data item from the distribution falling into bin i,
k is the number of bins,
$x_{(1)}, x_{(2)}, ..., x_{(k)}$ are the upper bin boundaries ($x_{(0)} = 0$ and $x_{(\infty)} = \infty$),
n is the number of data samples in the data set.

The expected number of observations in a bin denoted by E_i can be calculated as:

$$E_i = n \Pr_i = 10 \qquad i = 1, 2, ..., k. \qquad \text{(B.2)}$$

Step 4: Divide data into the bins. We will denote the number of observed data in bin number i as f_i. All models which were considered were continuous due to the nature of the distributions we are trying to describe. Our data, however, is discrete as a result of the snap shots being taken at time instances and the times only being recorded to the nearest second. A question of bin boundaries therefore arises. It was decided to make our data continuous by spreading it evenly within 0.5 seconds of their discrete value (e.g., if 5 time values of 8 seconds in length were obtained, it is assumed that the time values were actually 4.5, 4.75, 5.0, 5.25, and 5.5 seconds long).

Step 5: Calculate the test statistics. The test statistics were calculated using the following formula:

$$x^2 = \sum_{i=1}^{k} \frac{(f_i - E_i)^2}{E_i}, \qquad i > 1, 2, ..., k . \tag{B.3}$$

Step 6: The null hypothesis is rejected if the value of x^2 from equation (B.3) is greater than X^2_α, a Chi-Square variable with k-1-m degrees of freedom where m is the number of parameters estimated. The significance level of the test performed α=0.15 is high compared to the traditional α=0.05. This was done in order to minimize the possibility of accepting an incorrect distribution.

Appendix C

Properties of the Negative-Exponential Distribution

The exponential law is used to describe the distribution of local call conversation times. The negative-exponential distribution plays a major role in telephone similar in nature to that portrayed by the Gaussian distribution in communication theory.

Here are presented several of the important properties of the negative-exponential distribution:

$$\Pr[t_c = t] = cdf_c(t) = 1 - e^{-\mu_c t}\,, \tag{C.1}$$

where $\Pr[t_c = t]$ is the probability that any randomly selected call holding time will equal or exceed length t_c and μ_c is the average call holding time of all customer calls.

Given that an arrival (i.e., a call attempt) occurred at $t = 0$ and no arrival in $(0, t)$, what is the probability of an arrival in $(t, t + \Delta t)$, (Fig. C.1)?

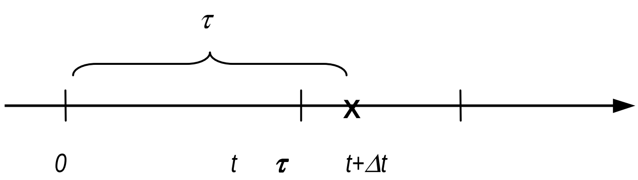

Figure C.1 **:** Properties of the negative-exponential distribution.

Assume that the interarrival times τ ate independent and identically distributed according to $cdf_c(t)$. We are interested in

$$\Pr_1 = \Pr[t < \tau \le t + \Delta t \mid \tau > t] = \frac{cdf_c(t + \Delta t) - cdf_c(t)}{1 - cdf_c(t)}\,. \tag{C.2}$$

The conditional arrival-rate is "roughly speaking" the probability of an arrival at t given an arrival at 0 and no arrival in $(0, t)$. When $cdf_c(t) = 1 - e^{-\mu_c t}$, one can se that the conditional arrival rate is μ_c . That is to say

$$\Pr_1 = \Pr[t < \tau \le t + \Delta t \mid \tau > t] = \mu_c \Delta t + O(\Delta t) \tag{C.3}$$

$$(O(\Delta t) \text{ is defined as } \lim_{\Delta t \to 0} \frac{O(\Delta t)}{\Delta t} = O\ )$$

is the probability of an arrival in (t, $t + \Delta t$) given that "we have waited" t units of time since the last arrival. Notice that this probability is independent of t; that is, **the negative-exponential process has no memory**.

In a similar fashion the conditional probability of no arrival in (t, $t + \Delta t$) is

$$\Pr_0 = 1 - \mu_c \Delta t + O(\Delta t) \tag{C.4}$$

and for two or more arrivals

$$1 - \Pr_0 - \Pr_1 = O(\Delta t)\ . \tag{C.5}$$

We have just seen that properties (C.3), (C.4), and (C.5) follow from the negative exponential distribution. If the times between arrivals are independent and identically distributed according to a cumulative distribution function $cdf_c^*(t)$ that satisfies (C.3), (C.4), and (C.5), then $cdf_c^*(t) = 1\text{-}e^{-\mu_c t}$.

Proof:

$$\frac{cdf_c^*(t+\Delta t) - cdf_c^*(t)}{1 - cdf_c^*(t)} = \Pr[t < \tau \le t + \Delta t \mid \tau > t] = \mu_c \Delta t + O(\Delta t)\ .$$

Hence,

$$\frac{cdf_c^{\prime}(t)}{1 - cdf_c^*(t)} = \mu_c \qquad \textit{and} \qquad cdf_c^*(t) = 1 - \mu_c \Delta t\ .$$

Property (C.3) implies that $cdf_c^*(t{=}0){=}0$ so that $\mu_c = 1$.

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