Delay Tolerant Networking in a Shopping Mall Environment

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A mio padre,

un bacio

Abstract

The increasing popularity of computing devices with short-range wireless offers new communication service opportunities. These devices are small and may be mobile or embedded in almost any type of object imaginable, including cars, tools, appliances, clothing and various consumer goods. The majority of them can store data and transmit it when a wireless, or wired, transmitting medium is available. The mobility of the individuals carrying such short-range wireless devices is important because varying distances creates connection opportunities and disconnections. It is likely that successful forwarding algorithms will be based, at least in part, on the patterns of mobility that are seen in real settings. For this reason, studying human mobility in different environments for extended periods of time is essential. Thus we need to use measurements from realistic settings to drive the development and evaluation of appropriate forwarding algorithms. Recently, several significant efforts have been made to collect data reflecting human mobility. However, these traces are from specific scenarios and their validity is difficult to generalize.

In this thesis we contribute to this effort by studying human mobility in shopping malls. We ran a field trial to collect real-world Bluetooth contact data from shop employees and clerks in a shopping mall over six days. This data will allow the informed design of forwarding policies and algorithms for such settings and scenarios, and determine the effects of users' mobility patterns on the prevalence of networking opportunities.

Using this data set we have analysed human mobility and interaction patterns in this shopping mall environment. We present evidence of distinct classes of mobility in this situation and characterize them in terms of power law coefficients which approximate inter-

contact time distributions. These results are quite different from previous studies in other environments.

We have developed a software tool which implements a mobility model for "structured" scenarios such as shopping malls, trade fairs, music festivals, stadiums and museums. In this thesis we define as structured environment, a scenario having definite and highly organised structure, where people are organised by characteristic patterns of relationship and mobility. We analysed the contact traces collected on the field to guide the design of this mobility model. We show that our synthetic mobility model produces inter-contact time and contact duration distributions which approximate well to those of the real traces. Our scenario generator also implements several random mobility models.

We compared our Shopping Mall mobility model to three other random mobility models by comparing the performances of two benchmark delay tolerant routing protocols, Epidemic and Prophet, when simulated with movement traces from each model. Thus, we demonstrate that the choice of a mobility model is a significant consideration when designing and evaluating delay-tolerant mobile ad-hoc network protocols.

Finally, we have also conducted an initial study to evaluate the effect of delivering messages in shopping mall environments by exclusively forwarding them to customers or sellers, each of which has distinctive mobility patterns.

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Here we are, this is one of those moments in which you suddenly realize that it is happening, the goals you have set at the beginning of your journey are about to come true. This is the moment in which the memories come up together to my mind and my thoughts go to all of those people who were part of this journey and assisted me to make it possible.

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Chapter 1

Introduction

A scientist in his laboratory is not a mere technician:
he is also a child confronting natural phenomena that impress him
as though they were fairy tales.

Marie Curie

This dissertation is concerned with human mobility as a fundamental factor for designing appropriate routing algorithms for infrastructureless mobile ad-hoc and delay tolerant networks in shopping mall environments. We present real-world measurement results from the mobility of people in such environments. The key contribution of this thesis is a mobility model for shopping mall environments which takes into account their distinctive mobility characteristics. We also present a mobility model generation tool which generates structured movement traces as well as implementing some traditional random mobility models. We define as structured environment, a scenario having definite and highly organised structure, where people are organised by characteristic patterns of relationship and mobility. A shopping mall is a good example of a structured environment as well as urban areas, built complexes, trade fairs, music festivals, stadiums, schools, airports, hospitals, etc.. This is a place where spatial and temporal aspects are well defined. A shopping mall is a collection of shops all adjoin a pedestrian area or an exclusive pedestrian street. It represents a relatively democratic space with all citizens enjoying access, with participatory entertainment and opportunities for social mixing. The built environment forms a spatial system in which, through principles of separation and containment, spatial practices are routinized and social relations are reproduced. Such an environment explicitly assume daily repeated local practices of individuals and groups of people with different roles. Various groups with different responsibilities and relationships with the environment are considered. While individual retailers may pursue their own strategies for profit within limited bounds, the mall operates as a whole to maximize pedestrian traffic by attracting the target consumers and keeping them on the premises for as long as possible. The association of regions with particular group membership, activities, and dispositions allows the individual to orient to the context and infer the appropriate social role to play. In many cases, shopping malls are tens of thousands of square meters in area and crowded much of the time. Because of their nature, such environments offer all of the elements required to build large-scale people-centric network applications.

In this chapter I outline the background issues that motivated this work, and state the research problems and contributions that are described in this dissertation. After that I give an overview of the contents of each chapter.

1.1 Background

Delay tolerant networking [3] is an approach to communication systems that seeks to address technical issues in heterogeneous networks, such as lack of continuous network connectivity mainly due to mobility and limited power, of wireless communication devices.

The acronym "DTNs" has been often used to identify either Delay- or Disruption-, or

Disconnection- Tolerant Networks, sometimes referring to one or the other without distinction. The InterPlaNetary Internet Special Interest Group were the pioneers in facing issues concerning delay experienced in transferring data between different planets of our solar system. The end-systems must have a free line of sight to be able to communicate since radio waves cannot pass through large solid objects such as planets and moons. In such an environment network protocols and algorithms, unlike the ones for terrestrial communications, have to support delay. Distance is a further problem in space communications since the intensity of electromagnetic radiation decreases according to $\frac{1}{r^2}$. These issues yield high bit error rates in addition to long term interruption which give rise to the term "disruption". In this scenario interruptions are somewhat predictable compared to unexpected disturbances which might occur in terrestrial networks where disconnections can be caused by natural disasters such as earthquakes, seaquakes, floodings, terrorist attacks, etc.

DTNs [4] were conceived for networks in which patterns of connectivity are known or predictable, such as space communication systems (LEO satellite) [5, 6, 7, 8], sparse mobile ad-hoc networks [9], infostation-based systems [10] and carrier based data collection in sensor networks [11]. However, they can also handle the unpredictable connectivity among mobile devices (e.g. PDAs) [12] and try to address most of the issues raised in the "network survivability" literature [13, 14] where networks lack continuous connectivity.

Intermittent connectivity, long or variable delay, asymmetric data rates, high error rate, high mobility, unknown mobility patterns, energy and storage exhaustion comprise just a few of the potential issues that make end-to-end communication unstable and unlikely in such networks. In these types of networks any synchronous communication paradigm does not perform well. Basic synchronous systems rely on a connected path between sender and receiver, and they negotiate communication parameters (such as clocks) at the data link layer before communication begins. On the other hands, asynchronous systems may simply transmit with no negotiation with the receivers. This may be required when the parties are not in the same portion of network. In fact, networks may be partitioned because nodes may not be in range with one another due to their physical distance and/or because of their mobility.

DTNs overcome such issues by using store-and-forward message switching [15]. In Wireless Sensor Networks (WSN) [16, 17] small and inexpensive devices can be networked together to enable a variety of new applications that include environmental monitoring, seismic structural analysis, data collection in warehouses, traffic monitoring etc. Sensors can be uniformly distributed or heterogeneously spread as islands separated by large distances. In these networks [18] mobile agents called MULEs (Mobile Ubiquitous LAN Extensions [19]) can be used to collect sensor data. MULEs can pick up data from sensors when in close range, buffer it, and drop it off at specific sinks when in proximity.

Mobile wireless sensor network systems have been proposed to gather and process information about wild animals across large regions with little communication infrastructure. The Princeton ZebraNet Project aims to track zebra migrations in Africa [20] [21]. Data collected by the sensors are forwarded from zebra to zebra using peer-to-peer protocols until it reaches a base station where it can be processed and analyzed. Notice that information are collected by researchers who are mobile and thus there is no fixed base station to which to send data.

Pocket Switched Networks (PSN) [1], which are a type of Delay Tolerant Network, use contact opportunities to allow humans to communicate without network infrastructures. PSNs make use of human mobility and local forwarding in order to distribute data. Information can be stored in the device and carried, taking advantage of the user's mobility, or forwarded over a wireless link when an appropriate contact is met. Such networks combine the fields of mobile ad-hoc networking and delay-tolerant networking. Examples of forwarding algorithms designed for such networks are BUBBLE Rap [22] and its improvement BiBUBBLE [23] which exploit social information for making forwarding decisions.

1.2 Research Problem and Thesis Contribution

DTN nodes may consist of powerful computers as well as laptops, PDAs, smartphones, pocket PCs, tiny sensors and any kind of network device. Nowadays such devices have become so wide spread that they can be considered pervasive in everyday life. They may be mobile, or embedded in almost any type of object imaginable, including cars, tools, appliances, clothing and various consumer goods. These may all communicate through increasingly interconnected networks. In these types of networks the fundamental assumptions used in mobile ad-hoc networking [24] [25] [26] and mesh networks [27] [28] cannot be adopted because an end-to-end path is never guaranteed. Instead, network devices must actively participate as part of an autonomic network, sharing wireless resources, providing local connectivity to other devices, and possibly offering local mobility management, persistent storage and forwarding services. They can provide connectivity based upon co-operation incentives or rewards, individual mobility and social patterns. A key requirement for the growth and robustness of such networks is the willingness to cooperate. Sometimes autonomic networks can be a better solution than traditional infrastructure-based networks because the latter can be more expensive, involve installation issues, incur customer cost, have particular policy restrictions, and may be less appropriate for people-centric networks where services are established on the fly.

The ultimate goal of this research area is to create a system that is pervasively and unobtrusively embedded in the environment, smartly connected, intuitive, effortlessly portable, highly scalable, and constantly available. In this context mobility plays a key role in the forwarding of data as it is mobility which gives rise to local connection opportunities when access to network infrastructure is not available or appropriate. Different patterns of mobility may give rise to different opportunity for communication, and different protocols may be more effective in particular situations. For this reason studying human mobility in different environments for extended periods of time is essential.

Recently, several significant efforts have been made to collect data reflecting human mobility. In this thesis we explore and characterize mobility in a shopping mall by gathering and analyzing Bluetooth contact traces. We conducted a field trial in a shopping mall in which twenty-five shopkeepers and clerks carried smart phones able to detect and log Bluetooth contacts over six consecutive days. This deployment was enough to sense continuously Bluetooth connectivity in more than half of the entire mall. Similar experiments have been done in different settings: a conference environment which involved conference attendees [2], in roller blade tours by exploiting skaters [29], in an office environment in which participants were working on the same floor in a building [30], in a research lab and university by involving researchers and students [1, 31, 32, 33, 34]. Following ethical principles, an anonymised version of our data is available to other research groups upon request. Several research groups have expressed interest on this data set which has already been made available to Dr Naranker Dulay from the Distributed Software Engineering Section of the Department of Computing at the Imperial College London, Shasha Zhou from the Hunan University in China and Soumaia Al Ayyat from the American University in Cairo.

Understanding of user mobility patterns is becoming increasingly important as it can guide the design of network applications and routing protocols. Moreover, realistic user mobility models reproduce more lifelike simulation scenarios which consequently lead to more trustworthy outcomes. Our field trial allowed us to analyse the collected contact traces and characterize aspects of human mobility in their environment.

In order to test routing protocols in shopping mall environments, we needed a model to represent human mobility in such places. The majority of existing mobility models, such as the Random Way Point mobility model [35], generate purely random movements that are very different from those observed in the real world and can produces meaningless colocation patterns [36, 31].

Several basic approaches have been proposed to design mobility models reproducing real world mobility patterns (see Section 3.2.1 for more details). Mobility models have been proposed based on social network theory by Musolesi et al. [37, 38], Venkateswaran et al. [39] and Herrmann [40]. This approach is based on the assumption that mobile devices are commonly carried by humans, so the movement of such devices is necessarily based on human decisions and socialization behaviour. Rhee et al. [41] presented a mobility model which generates movement traces based on Levy Walks which approximates real world traces. Ekman et al. [42] presented the Working Day movement model, a new movement model for delay tolerant networks, which intuitively presents the everyday life of average people that go to their workplace in the morning, spend their day at work, and commute back to their homes at evenings. Minder et al. [43] used the same approach focusing on office environments. The Time-Variant mobility model presented by Hsu et al. [44] is similar. In this model, nodes move to different square at different times of day in a periodic manner. In a recent work Mei et al. [45, 46] presented a simple mobility model, SWIM (Small World In Motion). This model is based on the simple assumption that people go more often to places not very far from their home and where they can meet a lot of other people.

The majority of the existing mobility models capture different mobility characteristics at a high level of abstraction. The mobility models proposed by Ekman et al. [42] and Minder et al. [43] tries to capture several mobility characteristics at a lower level than many other models. In this thesis we present a mobility model which is part of this effort. We have decided to narrow down the playground scenario to structure environments, with particular regard to shopping malls, and to focus on compelling applications in such environments. For this reason, we have designed a novel mobility model based on real traces [47, 48]. This relies on the simple observation that individuals follow relatively predictable trajectories within urban areas, shopping centres, malls, settlements and built complexes [49]. Architecture structures the system of space in which we live and move. In doing so, it has a direct relation to social life, since it provides the material preconditions for the patterns of movement, encounter and avoidance which are the material realization, or even the generator, of social relations [50, 51].

Human societies use space as a key and necessary resource in organizing themselves. The process of configuring space turns it from continuous into a connected set of discrete units which allows the application of different labels to its individual parts. These parts of the space can identify distinguishable groups, communities, or activities, and be associated with different rules of behaviour and conventions. An existent social structure can be mapped onto the configured space. The demarcation of boundaries allows particular relationships of access or visibility to emerge among the component spaces, and this in turn generates probabilistic patterns of movement and encounter within the population [52]. The model generates movements that are based in part on the surrounding architectonic structure. From the collected contact traces we derived cumulative distribution functions describing the mobility behaviour of customers and sellers; these distributions are important parameters for our Shopping Mall mobility model. Together with settings defining the environment, such as the shopping mall plan and number of sellers in each shop, they are submitted to our scenario generator to produce synthetic mobility traces using the Shopping Mall model. We evaluate the realism of the generated movement traces by comparing derived characteristics, such as the contact duration and inter-contact times, with those derived from real traces and a derivative of the Random Way-Point mobility model.

We also compared our generated movement traces with three other unstructured mobility models by evaluating two benchmark delay tolerant routing protocols, Epidemic and Prophet, against each model.

We concluded our work of thesis by analysing the possibility of delivering messages in such environments by only forwarding them either to customers or sellers to understand better the potential role of message carriers belonging to groups with different mobility patterns. For that, we employed two semi-Epidemic routing protocols. Figure 1.1 summaries the above steps and shows the stages we have followed to conduct the research project presented in this work of thesis.

To summarise, the contributions of the thesis are the following:

- A valuable data set for the research community comprising Bluetooth contact traces from a real-world human mobility experiment in a shopping mall.
- A characterization of the properties of shopping mall environments extracted from this data set. We characterize mobility in shopping mall environments in terms of contact duration and inter-contact time, and study interactions among nodes. The extracted distributions show evident distinctions from those presented in previous studies in different environments. Moreover, we identify two distinct patterns of mo-

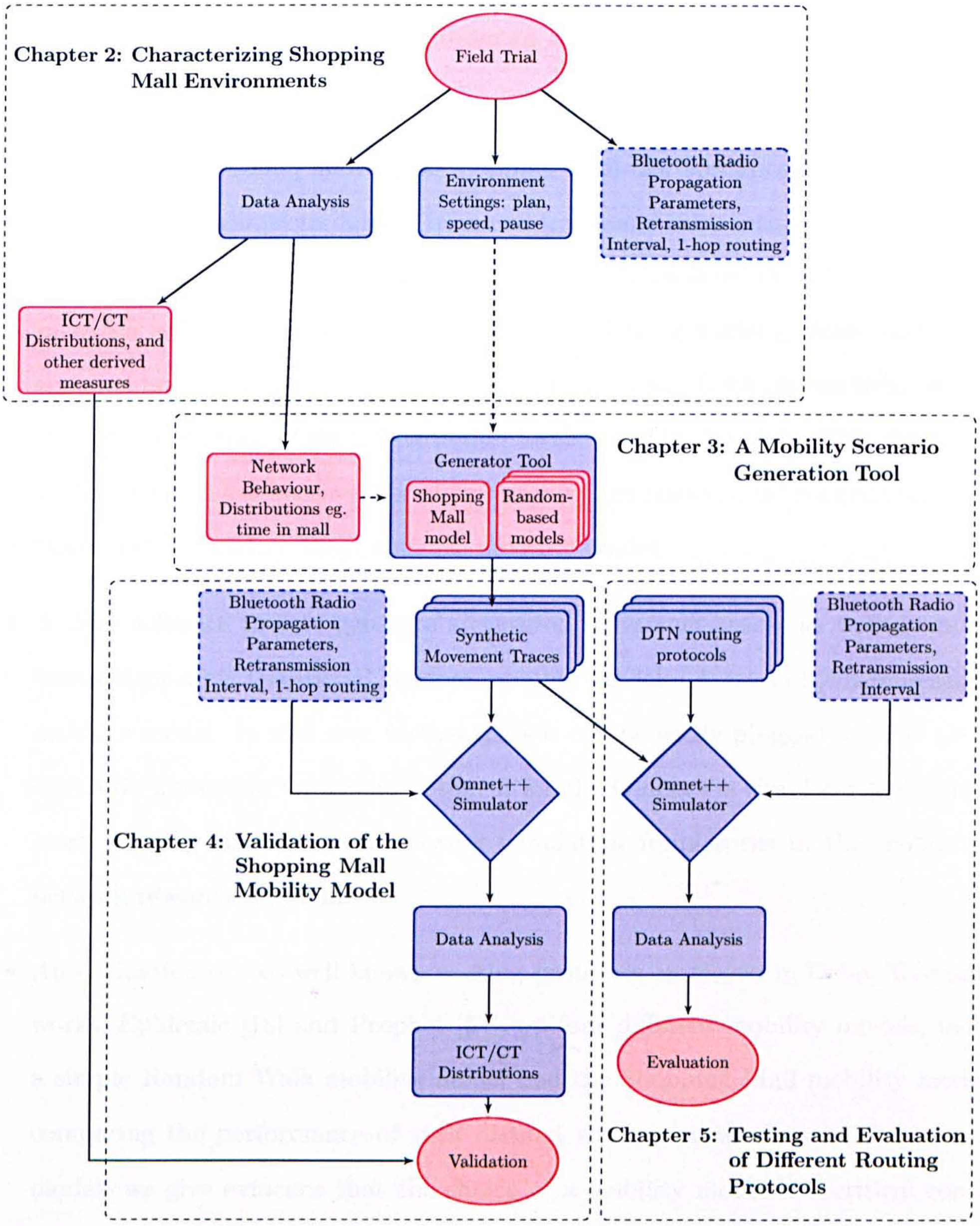

Figure 1.1: Main activities, artefacts and dependencies of my thesis.

bility related to two classes of individuals that we name *customers* and *sellers*, and present the technique we used to recognize them. While such classes of mobility may be intuitively obvious, we have presented objective evidence of their differences and some quantification of their nature.

- A *structured* mobility model for shopping mall-like scenarios which is founded on probability distributions derived from real traces and takes into account the plan of the environment. The extracted probability distributions drive the whole cyclic scenario in which sellers spend some time in and out of their working place, and customers spend time in different shops before leaving the mall. Both choose their destination with the assistance of shop "attraction levels" within the plan. This shopping mall mobility model has been validated by means of simulations and comparisons with real traces and a Random WayPoint-like mobility model.

- A Java software tool to generate structured movement traces as well as movement traces from some traditional random mobility models. A class object represents each mobility model. In this way, further models can be easily plugged-in. The generated synthetic movement traces are designed for the Omnet++ simulator [53], one of the most popular discrete event network simulation frameworks in the mobile ad-hoc network research community.

- An evaluation of two well-known routing protocols employed in Delay Tolerant Networks, Epidemic [18] and Prophet [54], on four different mobility models, including a simple Random Walk mobility model and the Shopping Mall mobility model. By comparing the performance of such distinct routing protocols on different mobility models we give evidence that the choice of a mobility model is a critical consideration in designing and evaluating of routing protocols for delay-tolerant mobile ah-hoc networks. We have also given evidence that traditional mobility models cannot be employed to adequately simulate "structured" scenarios.

- A variation of the Epidemic protocol which distinguishes between customers and sellers, and forwards messages through either one or the other. This allows us to understand better the role of groups of message carriers expressing different mobility patterns. We discuss the results of the simulations used for testing their performance in a shopping mall scenario. We have found that under particular circumstances it can be preferable to forward messages to one group of carriers rather than another.

1.3 Thesis Outline

The work presented in this thesis progresses through four stages. Firstly, we study human mobility in a shopping mall environment in order to better understand its intrinsic characteristics. Then, we exploit the peculiarities of this setting to design our mobility model for such an environment. This is validated by comparison with real-world traces. Finally, we test two delay tolerant routing protocols on four different mobility models. At the end of each chapter, we summarise its sections and discuss the novelty of our contribution.

The remainder of this thesis is organised as follows: in Chapter 2 we describe the capture and analysis of the traces of Bluetooth contacts in a shopping mall. We present various mobility-related characteristics of the data including contact duration and inter-contact time, study interactions among nodes, and highlight considerable differences in contact patterns between sellers and customers. We present evidence of distinct classes of mobility within the shopping mall and quantify this in terms of power law coefficients which approximate inter-contact time distributions. In Chapter 3 we present our shopping mall mobility model and a new mobility scenario generation tool which implements some traditional random mobility models as well as the shopping mall model itself. We describe specifications, design and implementation of our generation tool and all of the models available so far. In Chapter 4 we validate our mobility model by comparing its contact duration and inter-contact time distributions with those derived from real traces and the Random Way-Point[1] mobility model. In Chapter 5 we test and compare the performance of two delay tolerant

[1]It is a derivative of the Random Way-Point as it also considers inter-arrival times for customers.

routing protocols, Epidemic and Prophet, on four different mobility models [2], one of which is our shopping mall mobility model. We show that the mobility model used impacts on the performance of the two routing protocols and therefore that traditional mobility models cannot be employed to accurately simulate "structured" scenarios. In order to better understand the potential roles of customers and sellers, as message carriers. We evaluate the performance of two semi-Epidemic routing protocols which deliver messages by forwarding them exclusively through sellers or customers, respectively. In Chapter 6 we summarise the contributions of this work, express critical reflections and suggest possible further research directions.

[2] All of them are supposed to represent shopping mall scenarios. The Random Walk and the Random Way-Point mobility models have been used in previous study to simulate mobility in different settings.

Chapter 2

Characterization of Contact Opportunity in Shopping Mall Environments

People today only know how to live in society, not in community.
The soul of society is the law.
The soul of the community is love.

Roberto Rossellini (Europa '51)

In this chapter we firstly describe the experimental setup that we conducted in a shopping mall to collect Bluetooth contact data in order to measure human mobility patterns in this scenario.

Such contact traces helped us to characterize mobility in shopping mall environments in terms of contact duration and inter-contact time, and analyse interactions among nodes. Moreover, we identify two distinct patterns of mobility in shopping malls related to two classes of individuals that we name customers and sellers. Such characteristics introduce some implications for the design of both mobility models and forwarding algorithms for mobile ad-hoc delay tolerant network applications in environments such as this. In the next chapter we present our Shopping Mall mobility model based on statistical distributions derived from the captured contact traces. Ultimately, we evaluate our model by comparing its simulation traces with the collected real traces.

2.1 Related Work

Personal wireless devices are becoming increasingly popular. They are able to participate actively as part of an autonomic network, sharing wireless resources and providing local connectivity to other devices. It is thus becoming increasingly important to understand user mobility patterns. Such an understanding would guide the design of applications geared toward mobile environments (e.g., pervasive computing applications) and would help to improve simulation tools by providing more realistic user mobility models. The majority of work on delay-tolerant networks, mobile ad hoc networks and opportunistic networks relies on simulations, which, in turn, rely on realistic movement models for their credibility.

In the past, many synthetic mobility models have been adopted (see [35] for a survey of them) to run simulations. However, synthetic movement models are not very reliable because they are based on random mechanisms which show properties (such as the duration of the contacts between the mobile nodes and the inter-contacts time) very different from those extracted from real scenarios. This analysis is confirmed by the examination of the available real traces.

Even though real traces identifying user mobility would be preferable for evaluating the characteristics of mobile ad hoc network protocols, it is very difficult to trace nodes' movement in real large-scale mobile environments. Several studies have recently been performed in different settings: a conference environment involving conference attendees at

Infocom 2005 [2], in research labs and universities in Cambridge [1, 31] and MIT [32] involving researchers and students, during a Paris roller blading event [29], in a typical office environment [30, 43], from traces collected in the campuses Wi-Fi access network of Dartmouth College [33], UCSD [55], ETH Zurich [34], and from traces of a data set consisting of the mobility patterns recorded over a six-month period for 100,000 individuals selected randomly from a sample of more than 6 million anonymized mobile phone users [56]. Hsu et al. [57] propose a generic framework that capture preferences in choosing destinations to characterize pedestrian mobility patterns in a campus environment, and Tuduce et al. [58] present a structured framework for extracting the mobility characteristics from a WLAN trace. But apart from these examples, real movement traces have rarely been used for evaluation and testing of protocols and systems for mobile networks. Moreover, these traces are limited in size and scope, and from specific scenarios which make their validity difficult to generalize. They also do not provide other key information such as the distribution of the speed or the density of the hosts. Currently, CRAWDAD (the Community Resource for Archiving Wireless Data At Dartmoutha [59]) is the leading repository of publicly available wireless traces for the research community. This archive has the capacity to store wireless trace data from many contributing locations and to develop better tools for collecting, anonymizing, and analyzing the data.

Connection opportunities can be measured in terms of contacts by considering inter-contact time and contact duration. This is related to the frequency with which packets can be transferred between networked devices (as defined by the authors in [1]). Inter-contact time is the elapsed time between two non-consecutive sightings of the same node. This is the parameter that has the most significant impact on the feasibility of opportunistic networking. It (with contact time) determines the frequency and the probability of being in contact with the recipient of a packet or a potential forwarder in a given time period. Contact time is the duration of a single set of consecutive sightings of the same node, i.e. a presumed period of continuous contact. These indicators are particularly relevant in mobile ad hoc networking and in particular in mobile ad-hoc delay tolerant networks [60, 61].

The four data sets (from UCSD [55], Dartmouth [33], Intel and Cambridge) analyzed by [1] show surprising common statistical characteristics, such as the same distribution of the duration of the contacts and inter-contacts intervals. They show the same approximate power law, as evidenced by the straightness of the inter-contact time distribution on log-log scale plots. This is contrary to the exponential decay of many mobility models which means that the tail distribution function decreases faster. Out of this, networking algorithms in such environments, designed around exponential models such as random waypoint or random walk and all their derivatives, must be re-evaluated. [1] also describes how many existing forwarding algorithms perform badly in the presence of the power law mobility profile for inter-contact time, particularly for coefficients less than one.

The characteristics of seven data sets explained below, along with ours, are shown in the Tables 2.1 and 2.2. These data sets include different user populations, using three different wireless technologies. The mobile phone and iMote experiments have the advantages that the logging takes place wherever the user is and not just when the users are near access points. The GSM cell tower and WiFi-based experiments have larger user populations and durations, and include all contacts accurring at the infrastructure locations. Features like duration and periodicity of the experiments also affect the quality of data sets. In particular, observation of short event lengths is limited by the granularity of measurement. Similarly, events lasting longer than the experiment cannot be observed.

- *Intel* included seventeen researchers and interns working at Intel Research Cambridge. Because of real world factors which contributed to the malfunction of some of the iMotes, only eight of them yielded useful data.
- In *Cambridge* eighteen iMotes were distributed to doctoral students and faculty comprising a research group at the University of Cambridge Computer Lab. Due to malfunctioning of some of the devices, the experiment resulted in data from twelve iMotes.
- In *Infocom*, the devices were distributed to attendees of the Infocom student workshop.

Data Set	Device	Network type	User Communities	Environment	Geographical Location
Intel	iMote	Bluetooth	Researchers, Interns	Daily User Activity	Cambridge (UK)
Cambridge	iMote	Bluetooth	Students, Faculty	Daily User Activity	Cambridge (UK)
Infocom	iMote	Bluetooth	Conferees	Conference	Miami (USA)
UCSD	PDA	WiFi	Fixed Nodes	University Campus	San Diego (USA)
Dartmouth	Laptop, PDA	WiFi	Fixed Nodes	University Campus	Dartmouth (USA)
MIT Bt	Cell Phone	Bluetooth	Students, Faculty	Daily User Activity	Cambridge (USA)
MIT GSM	Cell Phone	GSM	Cell Towers	University Campus	Cambridge (USA)
Mixed Reality Lab	Smart Phone	Bluetooth	Shop Keepers, Fixed Nodes	Shopping Mall	Lecce (Italy)

Table 2.1: Comparison of data collected in eight experiments.

Data set	Network type	Duration (days)	Granularity (seconds)	Number of Devices	Number of internal contacts	Recorded external devices	Number of external contacts
Intel	Bluetooth	3	120	8	1,091	92	1,173
Cambridge	Bluetooth	5	120	12	4,229	159	2,507
Infocom	Bluetooth	3	120	41	22,459	197	5,791
UCSD	WiFi	77	120	273	195,364	N/A	N/A
Dartmouth	WiFi	114	300	6648	4,058,284	N/A	N/A
MIT Bt	Bluetooth	246	300	100	54,667	N/A	N/A
MIT GSM	GSM	246	10	25	572,190	N/A	N/A
Mixed Reality Lab	Bluetooth	6	120	25	284,492	749	60,223

Table 2.2: Comparison of data collected in eight experiments.

Participants belongs to different social communities (depending on their country of origin, research topic, etc.). For four consecutive days they all attended the same event and most of them stayed in the same hotel.

- *UCSD* and *Dartmouth* make use of WiFi networking, with the former including client-based logs of the visibility of the access points, while the latter includes SNMP logs from the access points. In this case, assuming that mobile devices in sight of the access point would also be able to communicate directly (in ad hoc mode) introduces inaccuracies. It is overly optimistic, since two devices attached to the same access point may still be out of range of each other. However, two devices may pass together at a place where there is no instrumented access point and this contact would not be recorded. Despite these inaccuracies, the WiFi traces are a valuable source of data, since they span many months and include thousands of nodes. Another potential issue with these data sets is that the devices are not necessarily co-located with their owners at all times, i.e. they do not always characterise human mobility.

- *MIT Bt* and *MIT GSM* are data sets from the Reality Mining project at MIT Media Lab and include traces of visible Bluetooth devices and GSM cell towers respectively. They were from 100 cellphones distributed to students and faculty on the campus during nine months. Also for the *GSM* data set, like for *UCSD* and *Dartmouth*, assuming that two mobile phones in sight of the same cell tower would be able to communicate directly introduces inaccuracies. They may still be out of range of each other. Furthermore, it hard to ensure that the phones are in fact co-located with their owner at all times.

- *Mixed Reality Lab* is the data set that was used for the work of this thesis. Its features are described later in this chapter (see Sections 2.3 and 2.4).

2.2 Shopping Malls: Background

Shopping is one of the most important contemporary social activity [49]. Despite increases in catalogue sales, shopping remains essentially a spatial activity and the shopping centre is its chosen place. The time spent in such shopping malls by people is second only to that spent at home and at work or school [62]. Shopping centres have already become tourist destinations, complete with tour guides and souvenirs, and some include hotels so that vacationers and conferees need not to leave the premises during their stay. Moreover, planned retail space is colonizing other privately owned public spaces such as hotels, railway stations, airports, office buildings and hospitals, as shopping has become the dominant mode of contemporary public life [49]. While individual retailers may pursue their own strategies for profit within limited bounds, the centre operates as a whole to maximize pedestrian traffic by attracting the target consumers and keeping them on the premises for as long as possible.

The shopping centre represents a relatively democratic space with all citizens enjoying access, with participatory entertainment and opportunities for social mixing. The built environment forms a spatial system in which, through principles of separation and containment, spatial practices are routinized [63] and social relations are reproduced. The association of regions with particular group membership, activities, and dispositions allows the individual to orient to the context and infer the appropriate social role to play. Fiske et al. [64] describe an example of the vertical structuring of mall space according to the social status of the targeted consumers. The built environment is, therefore, socially and psychologically persuasive [65]. Excellent analysis of the contemporary shopping mall may be found in [49].

Because of their nature, such environments offer all of the elements required to build large-scale people-centric network applications. A mobile ad-hoc delay tolerant network is an autonomous system of mobile devices intermittently connected by wireless links forming an arbitrary graph. Because of the devices' intrinsic mobility the topology of the network is time varying. Such a network may operate in a standalone fashion, or may be connected to the larger Internet. Mobility plays a key role in the forwarding of data as it is mobility which gives rise to local connection opportunities when access to network infrastructure is not available, expensive, involves installation issues, incurs customer cost, has particular policy restrictions, or may be a poor fit for services that are established on the fly. Note that connectivity to traditional networks is not always better than local connectivity; local networking can be better if the corresponding party is nearby, either because one or both of the terminals do not have access to the network infrastructure, or because this is expensive. Ad-hoc networks are fully decentralized and can work in any place without any infrastructure. In fact, mobile nodes that are in radio range of each other can directly communicate, whereas others need the aid of intermediate nodes to route their packets. This property makes these networks flexible and robust. However, the dynamic nature of the network topology introduces problems for the design of ad-hoc networks. Mobility compromises the communication between users, as forwarding paths may be unstable and receiver reachability may be very variable.

We believe that different environments are characterized by different patterns of mobility and should be supported by suitable embedded routing protocols. Therefore collecting data reflecting human mobility is important to design suitable routing protocols for applications for mobile ad-hoc delay tolerant networks. We suggest that a number of environments are characterized by a similar of mobility structure to shopping malls including trade fair, music festival, automobile race track, stadium, etc. Stores and shops in shopping malls correspond to stands, kiosks, booths, tents, bars, pubs, and so on in these correlate settings. Customers, audience, partygoers and any attending individual are the main actors who might be supported. Unfortunately, to date little work has been done to measure human mobility in this kind of setting. A shopping mall is a place where a collection of shops all adjoin a pedestrian area or an exclusive pedestrian street. In many cases, shopping malls are tens of thousands of square meters in area and crowded much of the time. Developers have exploited a modernist nostalgia for authentic community and have promoted the conceit of the shopping centre as an alternative focus for modern community life. Shopping malls look more and more like a world in microcosm. We could even spend the whole day there without necessarily doing shopping.

2.3 Experimental Setup

We have conducted an experiment to gather data about contacts between devices carried by humans in a shopping mall environment. Here we are focusing on human mobility in shopping mall environments. Ideally, a data set would cover a large user base over a large time period on connection opportunities. Setting up an experiment in such places is not easy: local regulations may prevent such an experiment, and even if permitted there are problems of privacy, security, mistrust, etc.

In order to find a shopping mall where they would let me run the experiment I asked for permission from marketing managers and shop keepers, in both the United Kingdom and Italy. It has been an "Odyssey". Initially, I started looking for a shopping mall in the city of Nottingham. I visited three centres but I was refused permission in each. The first marketing manager in charge of the shopping mall administration I asked rejected my request immediately without any reason more specific than: "*It is not allowed!*". Given this outcome I decided not to ask permission from the manager at the second mall; instead, I only asked shop keepers and assistants who were willing to take part at the experiment. At first this strategy appeared to be successful until I got back to my office to a message from the manager stating that the trial was NOT allowed. At the last mall, the manager allowed me to run the trial upon agreement with the shop employees. Unfortunately, few employees wanted to participate in the experiment. One shop keeper's reason for not allowing me to run the experiment in his shop was: "*Such devices can steal customers' credit card numbers when they pay!*". I was about to give up, conscious that it would have been very hard or even impossible to find a shopping mall in which to run my experiment. I realised that such tight internal regulations were a reason for which there are few similar studies. I also went to ask for permission in some shopping centres in the city of Bologna but without success, mostly because of mistrust from the shop keepers. At last, I tried in a shopping

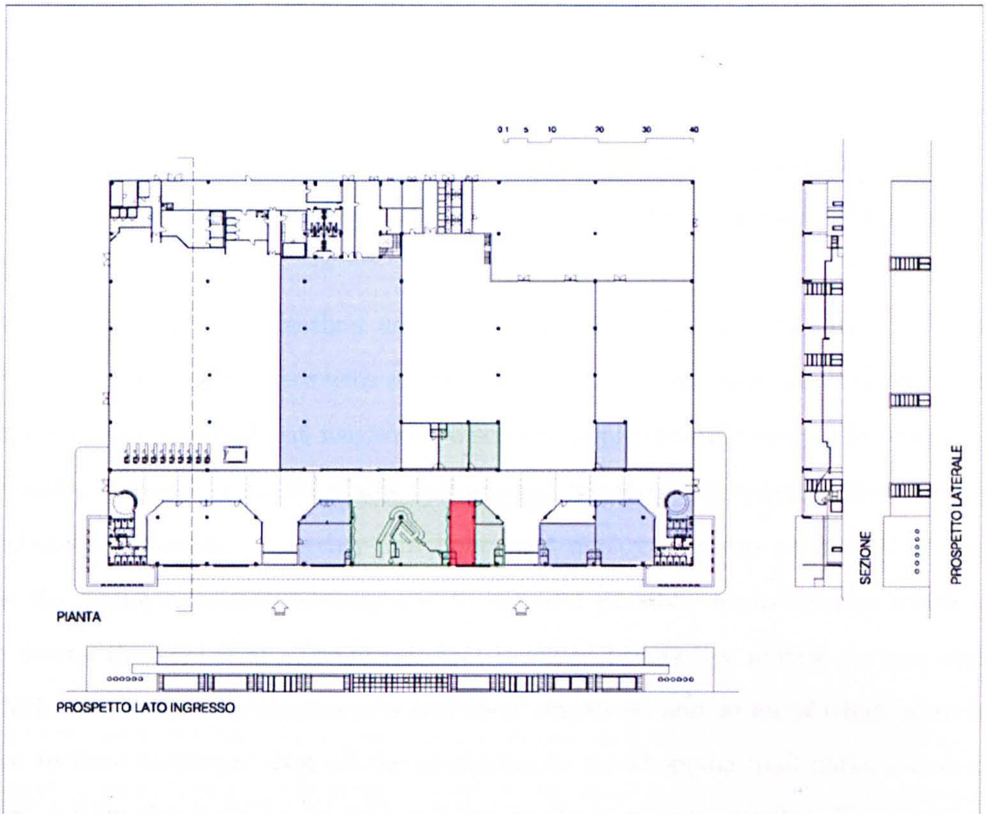

Figure 2.1: Plan of the shopping mall - 11 shops, 1 store, 1 bar and 18 mobile devices, 7 fixed devices involved in the experiment

mall in my hometown in Lecce where two friends of mine were working there as clerks. Using their contacts I managed to get enough shop keepers involved. By being a part of my friends', and therefore the shopkeepers' "community", I was able to gain their trust so as to make them feel comfortable to participate in the experiment. Finally, I made it! I informed the participants about the purpose of such an experiment, the procedure with which it was conducted, and provided them with the requested information following all the ethical principles. I did not force participants to get involved into the experiment. I received a conscious consent of the subjects involved in the experiment and also informed the manager of the whole shopping mall about the field trial. Furthermore, we also took into consideration all possible risks and obstructions that the participants of the experiment might face.

We adopted the same method used by [1], [31] and [2] to collect data. For that, we provided some shop employees with smart phones running symbianOS and using Bluetooth technology. They carried out neighbour discovery approximately every 120 seconds. The Bluetooth 1.1 specification [66] states that an inquiry process for neighbor discovery should last about ten seconds. A twenty-four hour pilot deployment was performed in order to refine the deployment methodology and to consider possible inconveniences which might arise during the field trial. The experiment involved twenty-five mobile devices, eighteen of which were carried by shopkeepers and shop employees and seven of which were static, placed in fixed locations. Not all the employees in the shopping mall participated in the experiment but the ones who did were sufficient to obtain valuable results. Their deployment was enough to sense continuously Bluetooth connectivity in more than half of the entire mall. For six days these devices were given to the participants at around the same time, 9:15 am, and collected at 8:45pm. They carried the devices throughout the working day (from 09:00am to 01:00pm and from 04:30pm to 09:00pm). The phones were deployed in one store, eleven shops and one bar. The floor plan in Figure 2.1 shows the shopping centre, which has a surface area of $10,880m^2$ (without considering the parking area)[1].

[1]We are very thankful to Dr. Mauro Lazzari and Dr. Gianluca Galati, the architects who provided us the plan of the shopping mall

Even though there is a range of useful data sets available (in the Tables 2.1 and 2.2 it is shown a summary of the features of our and seven more data sets), no one deals with shopping malls in particular. Therefore, to design a mobility model for such an environment we conducted an experiment for our data capture. The *Mixed Reality Lab* data set shown in the Tables 2.1 and 2.2 has been used for the work of this thesis. This includes Bluetooth contact traces recorded in a shopping mall which is a more defined structured environment with respect to the others listed in Table 2.1. Such traces have been collected by both mobile and fixed nodes. The former are some shop keepers during their working time while the latter are Bluetooth devices left still in some shops. This data set includes handheld Bluetooth devices employed in a smaller scale environment with short granularity for few days. The duration of the experiment, which is longer than some others, and the sufficient number of devices deployed make our data set comparable with the existing ones. It is interesting noticing the high number of contacts with a relatively smaller number of devices with respect to the other data sets. These values prove that this is a valuable data set and present shopping malls as appealing environments for delay tolerant mobile ad-hoc networks.

2.4 Analysis of Shopping Mall Mobility Patterns

We conducted our experiment in a shopping mall in order to provide base-line data to support the design of forwarding algorithms and the generation of a realistic mobility model for such scenarios. All of the twenty-five smart phones that we deployed in the shopping mall yielded useful data. Each one of our smart phones records in its log file the scanning time, that is, once every 120 seconds [2], its own MAC address and all detected MAC addresses:

```
<time, own MAC address, [detected MAC address]>
```

[2]They cyclically carried out neighbor discovery every 120 seconds after the end of the last scanning. The Bluetooth 1.1 specification states that an inquiry process for neighbor discovery should last about ten seconds. In our case, it lasts 14 seconds.

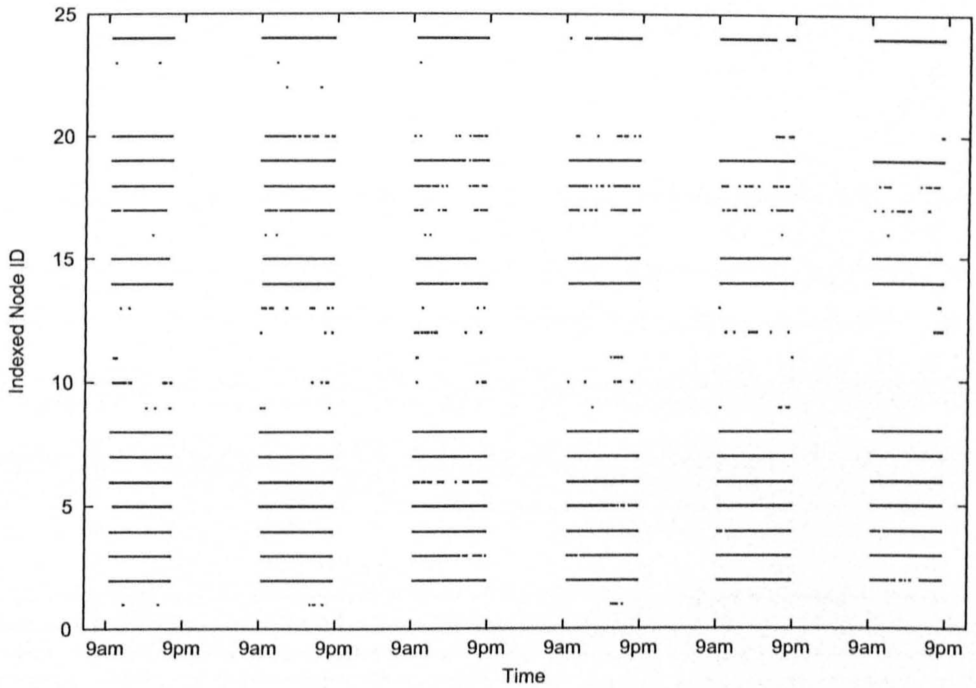

Figure 2.2: Time series of contacts seen by one Smart Phone of other trial Smart Phones over six working days.

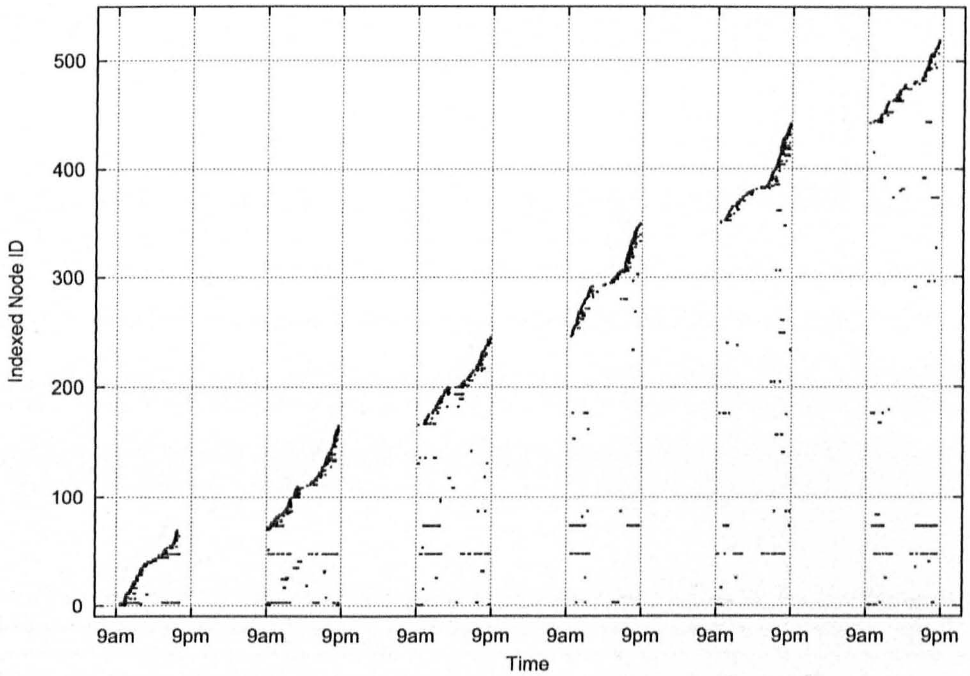

Figure 2.3: Time series of contacts seen by one Smart Phone of all other devices over six working days.

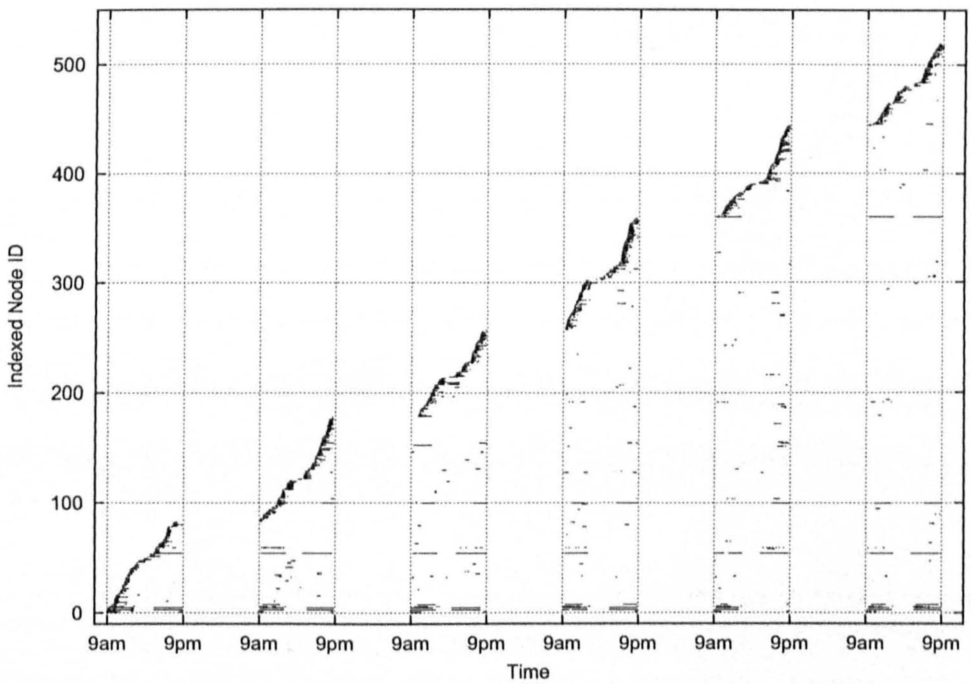

Figure 2.4: Time series of external contacts seen by all of our Smart Phones over six working days.

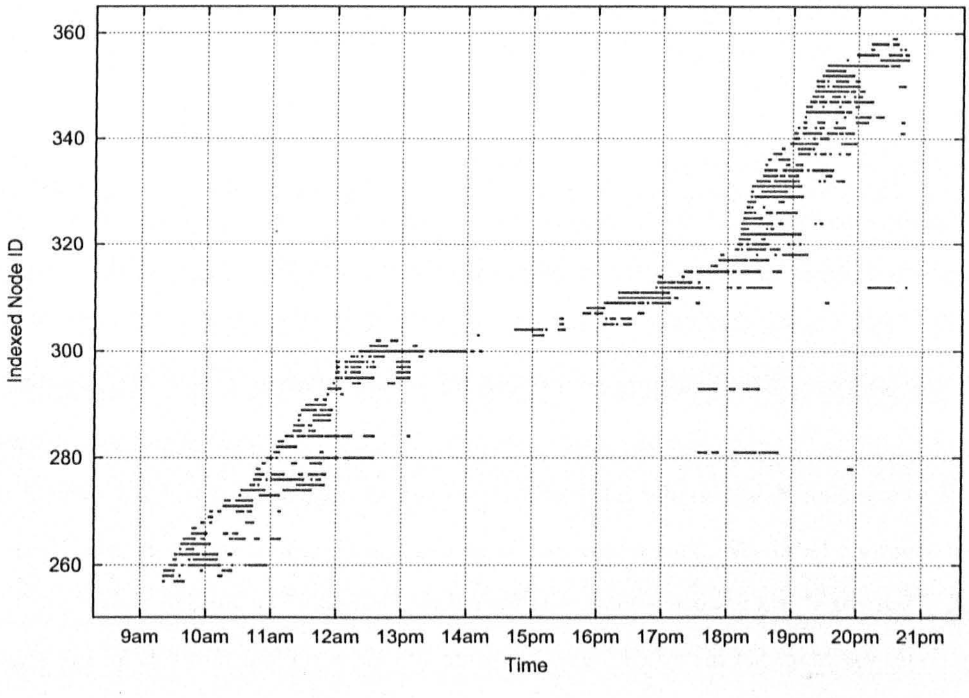

Figure 2.5: Time series of contacts seen by one Smart Phone of all other devices over the fourth day.

For example:

```
...
32498 ********5d08 ********60b6 ********6e65 ********5d0e
32632 ********5d08 ********60b6 ********0f01 ********5d0b ********6e65
********5d0e
32766 ********5d08 ********6e65 ********5d0e ********abc5
32900 ********5d08 ********6e65 ********abc5
33034 ********5d08 ********6e65
...
```

Clock synchronization was checked manually. We processed the log files by means of shell scripts to skim data, extract useful information and conduct statistical analysis. We have also made extensive use of `R` [67], a free software environment for statistical computing and graphics, to perform statistical analysis and produce the respective plots. Besides `R`, we used `gnuplot` [68], a portable command-line driven graphing utility, to generate further graphs.

A typical log file is visualized in Figures 2.2 and 2.3 where the X-axis shows the time and the Y-axis identifies unique Bluetooth MAC addresses seen. We label contacts between two of our smart phones as "internal" whilst all the other contacts are "external". Internal contacts are all the contacts between our smart phones. External contacts are much greater in number than internal contacts and represent a valuable source of data: they are the other Bluetooth devices seen in the vicinity of our smart phones, and allow us to estimate the deployment and movement of other Bluetooth devices in the mall.

The smart phone taken into account for this analysis is the one whose MAC address ends with "**c3a4**" located in the shop highlighted in red in Figure 2.1 and used as fixed node. The plot in Figure 2.2 shows internal contacts, i.e. between "**c3a4**" and the other 24 provided smart phones, while Figure 2.3 shows the external Bluetooth devices seen by "**c3a4**". Figure 2.4 shows the external Bluetooth devices seen by "**c3a4**" as seen by any of the twenty-five smart phones (519 external devices), while the plot in Figure 2.5

zooms in to the fourth day of the experiment. These last two plots show that most of the external contacts spend less than two hours in the shopping mall. Our devices recorded 60223 external contacts with 749 distinct devices and 284492 internal contacts between each other. There are significantly more external devices than internal ones, but they are seen less often. The maximum number of internal and external nodes seen by one of our devices at one time was respectively 18 and 11. Following ethical principals, an anonymised version of our data is available to other research groups on request (i.e. with MAC addresses mapped to synthetic IDs with only local relevance).

2.4.1 Inter-Contact and Contact Time

We analyze connection opportunities in terms of contacts by considering contact duration and inter-contact time. Our results are necessarily constrained by the duration and periodicity of the experiments. In particular, observation of short event lengths is limited by the granularity of measurement (around 120 seconds). Similarly, events lasting longer than the experiment cannot be observed. In Figure 2.6 we plot the inter-contact time distributions of two smart phones (identified with the last four digits of their MAC address) with different subsets of devices for the six days of the trial. One of the two smart phones has been used as fixed node (i.e. `c3a4`) and left next to the cash register (in the Figures 2.6-2.7 labeled as FX) in the red shop in Figure 2.1. The second smart phone (i.e. `7398`) has been employed as a mobile node and carried by a seller (in the Figures 2.6 and 2.7 labeled as M) based in the same shop.

In Figures 2.6 and 2.7 we show respectively inter-contact and contact times for the above mentioned smart phones. In each case four groups of devices are considered: external devices; all contacts; own 25 smart phones (i.e. all shop employees participating in the experiment and working in the shops highlighted in red, green and blue); and only neighboring smart phones (those highlighted in green in Figure 2.1). The figures also show that the fixed and mobile device have very similar distributions. This could be explained by employees being mainly located in the shop where they are during the working day and thus having

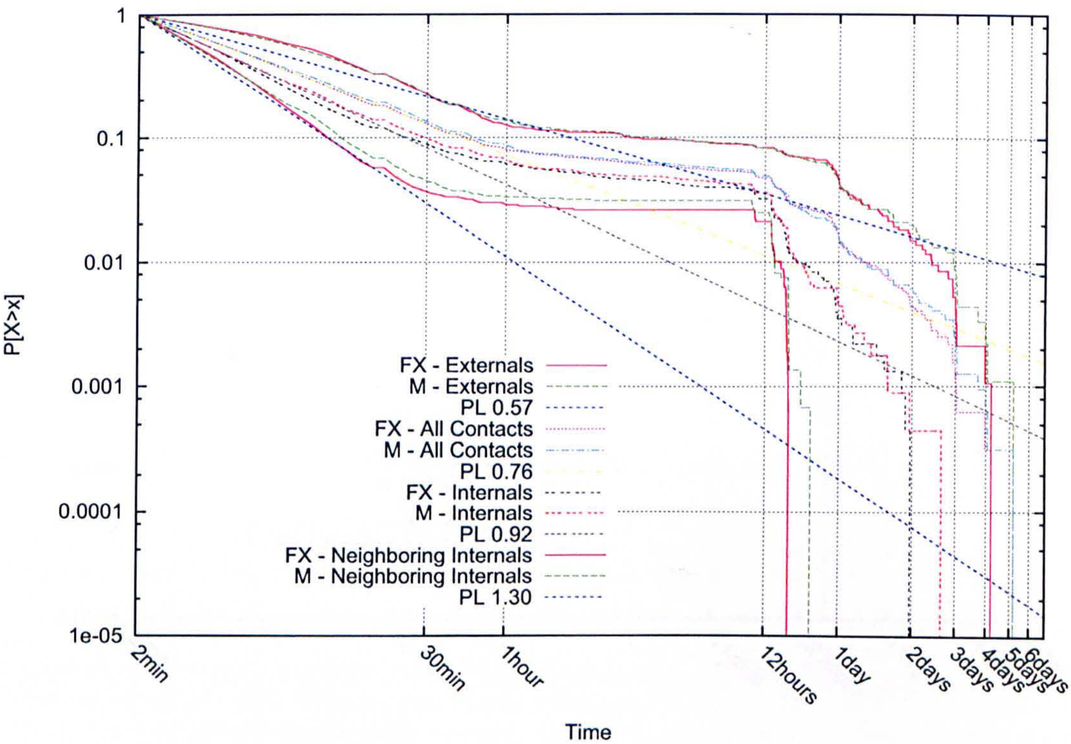

Figure 2.6: Tail Distribution Functions of the Inter-Contact Time over six days of the fixed node "c3a4" (FX) and mobile node "7398" (M) with: externals, all contacts, all 25 internal phones, and neighboring smart phones only.

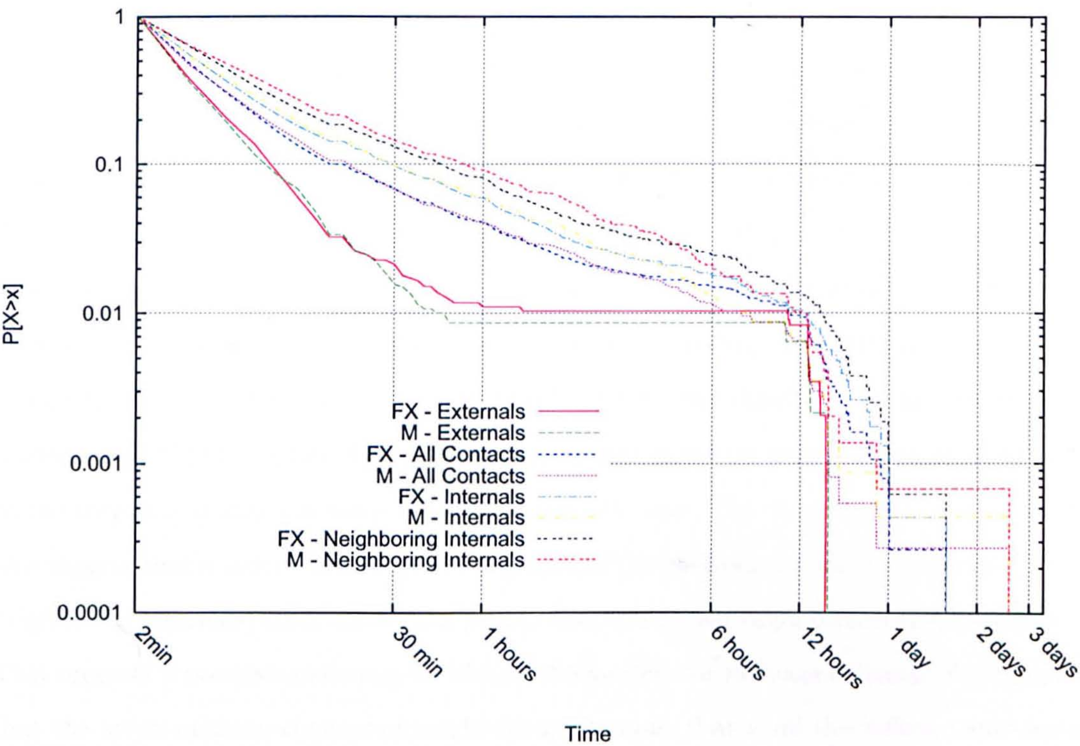

Figure 2.7: Tail Distribution Functions of the Contact Duration over six days of the fixed node "c3a4" (FX) and mobile node "7398" (M) with: neighboring internal phones only, all 25 internal phones, all contacts, and externals.

the same contacts in sight. All of them exhibit a strong heavy tail property which can be observed as an approximate power law for the time scale [2min:1hour] for the first three groups (i.e. externals, all contacts and all internals) with power law coefficients respectively 0.57, 0.76 and 0.92, and an approximate power law for the time scale [2min:30min] for neighboring shopkeepers. Note that the distribution for neighboring shopkeepers in Figure 2.6 shows a power law with coefficient 1.30. This may be significant because, using multiple intermediate relays, this is sufficient for stateless forwarding algorithms to converge [1]. After about one hour all of the graphs tend to plateau until the end of the working day. The shape of the distributions in Figure 2.6 shows us that inter-contact times tend either to be smaller than one hour or larger than twelve. This is most evident in the neighboring shopkeepers' distribution which is almost flat from around 60 minutes to 12 hours. This suggests that internals, namely, shopkeepers, sellers and shop assistants in the shopping mall, are in contact with each other most of the time allowing MANET-like connectivity. Longer inter-contact times are larger than twelve hours (the time between two consecutive working days). This implies that externals commonly spend up to an hour in any one part of the shopping centre and some come back the next day. The distributions in Figure 2.6 also suggest that a seller tends to meet subgroups of people from the same organization (i.e. neighboring internals) more often than people from a different organization (i.e. externals). This suggests a promising strategy to identify forwarders for message delivery. We imagine that the union of these clusters of neighboring internals, that is all the sellers, could form a reliable mobile ad-hoc network backbone in a shopping mall environment. This is backed up by Figure 2.7 which shows that the contact time distributions also approximate a power law distribution. Contact durations for externals are almost all smaller than 1 hour. It is worth noticing that a few external devices have very long contact durations which suggest that they could in fact be shop employees working close by rather than customers. This is backed up by the plot in Figure 2.8 showing any-contact durations of externals (externals' MAC addresses are numbered on the x-axis) with any of our smart phones. Hereby, we cannot assume a priori that externals devices are customers or individuals with no relation with the centre. We consider this in more detail in Section 2.5.

Notice that the order of the distributions in Figure 2.7 is reversed with respect to the order in Figure 2.6. The contrast between the distributions in Figures 2.6 and 2.7 and the corresponding distributions from previous experiments [1] and [2] suggest that the nature of the environment and the individuals has a significant impact (inter-contact time and contact duration distributions of previous field trials in campuses and conference environments are in Appendix A). We suggest that in campus and conference environments people have more freedom to move without particular constraints and boundaries, giving rise to longer inter-contact time than the ones seen in the shopping mall, where individuals follow certain motions strictly related to the surrounding environment and their aims. Figures 2.6 and 2.7 show that externals have a mobility pattern that is distinct from employees. In addition, externals tend to spend shorter periods in the shopping mall compared to people in campuses and conferences. Because of the purpose of their presence in the mall, externals, which are mainly customers, tend to stay close to sellers and the majority of them do not return on the same day. This behavior gives rise to shorter inter-contact times than in [1] and [2].

2.4.2 Inter-Any-Contact and Any-Contact Times

In the previous section we have analyzed contacts between pairs of devices, in terms of the frequency and duration of the contact. In this section we study the frequency (inter-any-contact time) and duration (any-contact time) of transfer opportunities between a subset of externals (those seen by the node 'c3a4') and our smart phones. We do not show the "inter-any-" and "any-"contact times for all smart phones because it appears that sellers are almost always in contact with neighboring sellers.

Figure 2.10 shows the any-contact time distribution for all of the externals seen by 'c3a4' with any internal node. As expected, any-contact times with externals are much longer than contact times but with the same distribution shape. It is also clear that some externals spend much more than one hour in the mall in total, even if they spend less than an hour near any single seller, which is an internal. Figure 2.9 shows inter-any-contact time

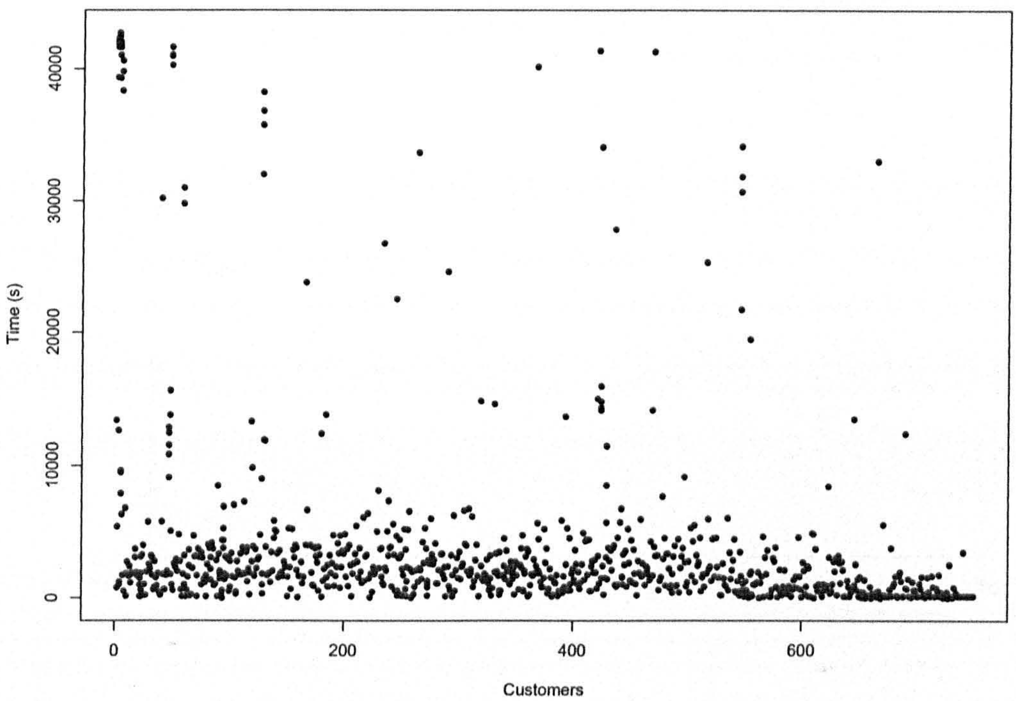

Figure 2.8: Time (in seconds) spent by externals in the mall.

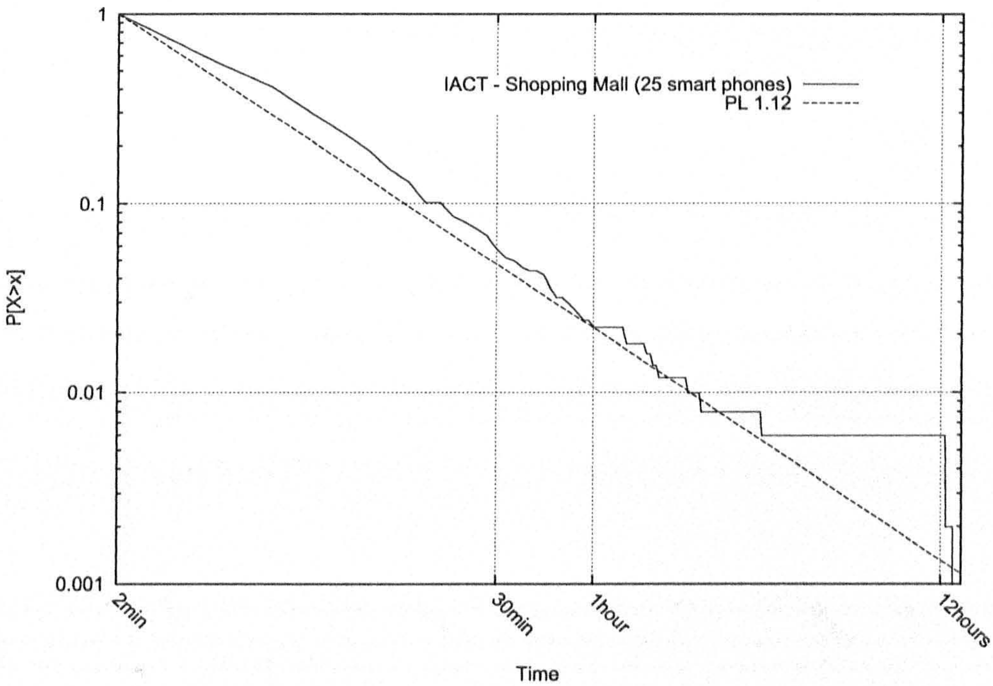

Figure 2.9: Distribution Function of Inter-Any-Contact Time over six days for the externals seen by the node 'c3a4' with any internal device.

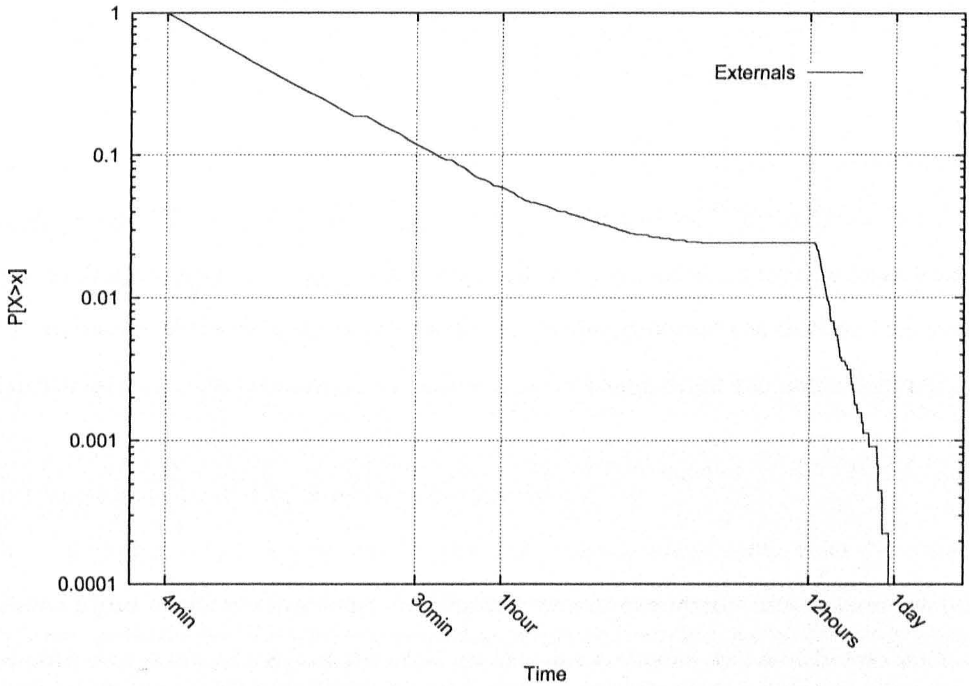

Figure 2.10: Distribution Function of Any-Contact Duration over six days for the externals seen by the node 'c3a4' with any internal device.

for the same externals with any internal node. Compared to Figure 2.6 the best fit power law coefficient increases from 0.57 to 1.16. This difference is quite relevant, in particular if compared to the results of [2]. As one might expect, a node willing to communicate with any member of a group of other nodes has much better forwarding possibilities. More generally, information about other groups of people could be exploited in application layer protocols. For example, a group of nodes subscribing to be "shop-members" might receive benefits in exchange for involvement in communication.

2.5 Identifying Two Main Mobility Patterns

In this section we seek to improve an understanding of the structure of human mobility in shopping malls [69] [70] by identifying different groups of mobility patterns to develop a corresponding mobility model. In previous studies, some mobility models have been based on the structure of the relationships among the people carrying the devices [37] [38] [71].

Human society can be divided in communities. Members of the same community may interact with each other preferentially. It has been argued that society is ruled by rules while community is ruled by love (see opening quote).

In a shopping mall, people should also take into account some rules because of the intrinsic nature of the environment. In this microcosm everyone's movements are bounded by his/her own role and his/her purpose. In this environment we identify two main classes of individuals with different mobility patterns. First, shop employees in charge of particular tasks (i.e. shopkeepers, sellers, clerks, shop assistants, etc.) are co-located in well defined locations whose mobility is defined by their duties. Second, customers who are free to move "wherever" they like and for their own specific purposes within the whole area.

By following the same metric used in [71] we measure the relationship between two people in a shopping mall by how many times they meet and how long they are in contact with each other. Here we provide the methodology to identify devices carried by visitors/customers and devices carried by shopping mall related people based purely on contact duration, inter-contact time and frequency. Namely, if an internal device, i.e. one of our smart phones, spends a long time in contact with an external device or they see each other very often then we might assume that they are in "working relationship". As such they have specific duties and relatively predictable mobility. Here we explore further properties of the real scenario and present statistics concerning the contact duration for "internal" and "external" devices. We consider number of contacts and contact durations to characterize the mobility traces. We identify contacts between two of our smart phones as "internal" whilst all the other contacts are "external".

While we know that internal contacts are between sellers, we cannot assume that external contacts are between sellers and customers because they might be between "our" sellers and any other seller's device (e.g. a sellers' personal phone). Figure 2.11 plots the number of contacts against the longest cumulative contact duration of each device with our smart phones, day by day, distinguishing between internal and external devices. We can see two clusters of devices: externals on the left bottom and internals on the right bottom of the quadrant. We infer that people in the first cluster do not spend more than roughly two hours in the shopping mall. Thus, we can infer that all the nodes falling in to this cluster are likely to be customers. Only 9 external devices out of 752 have higher contact duration and number of contacts. The majority of the remaining devices fall in the second cluster which means that they tend to spend a long time "together" and meet each other more often. That is expected sellers' and shopping mall employees' behaviour since neighbouring sellers tend to be in contact for long time. Shop employees tend to go out of their working place some of the time, for several reasons, e.g. lunchbreak, work, personal needs or to meet other colleagues. The more distant the working places are the more contact durations might decrease. This is strengthened by the bell shape of the distribution in Figure 2.12 which plots the number of contacts against contact duration for each device with all the internal devices. The "internal-like" nodes in Figure 2.12 are external devices behaving like internals. We conjecture that they are devices carried by other sellers in the mall which were not part of the experiment.

Furthermore, we analyze the longest inter-contact time against the highest number of

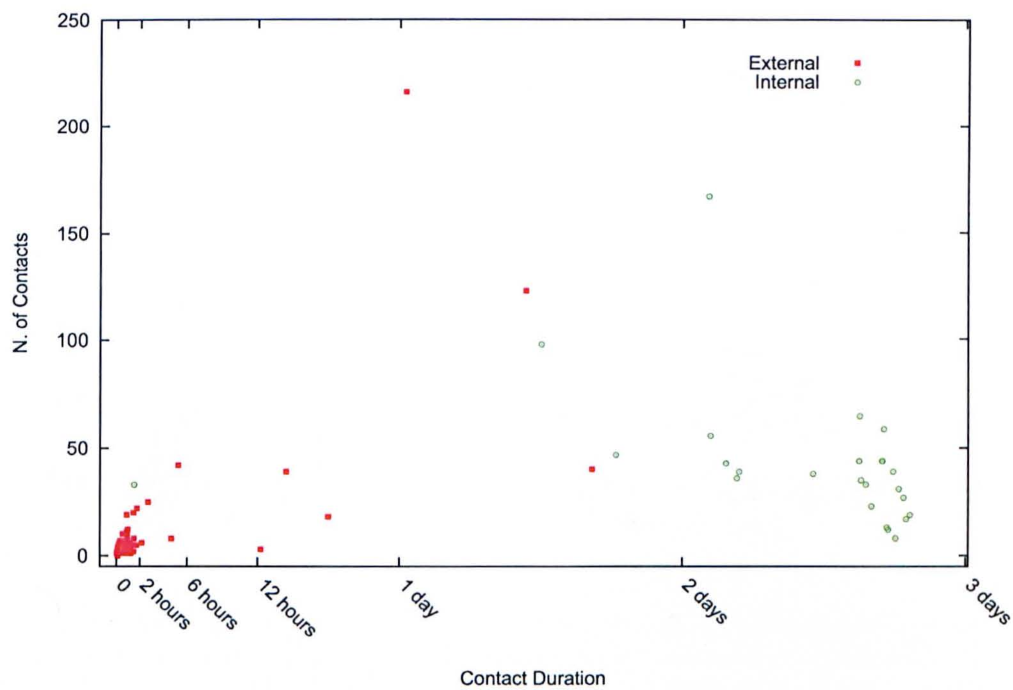

Figure 2.11: Number of contacts versus the longest contact durations for internal and external devices

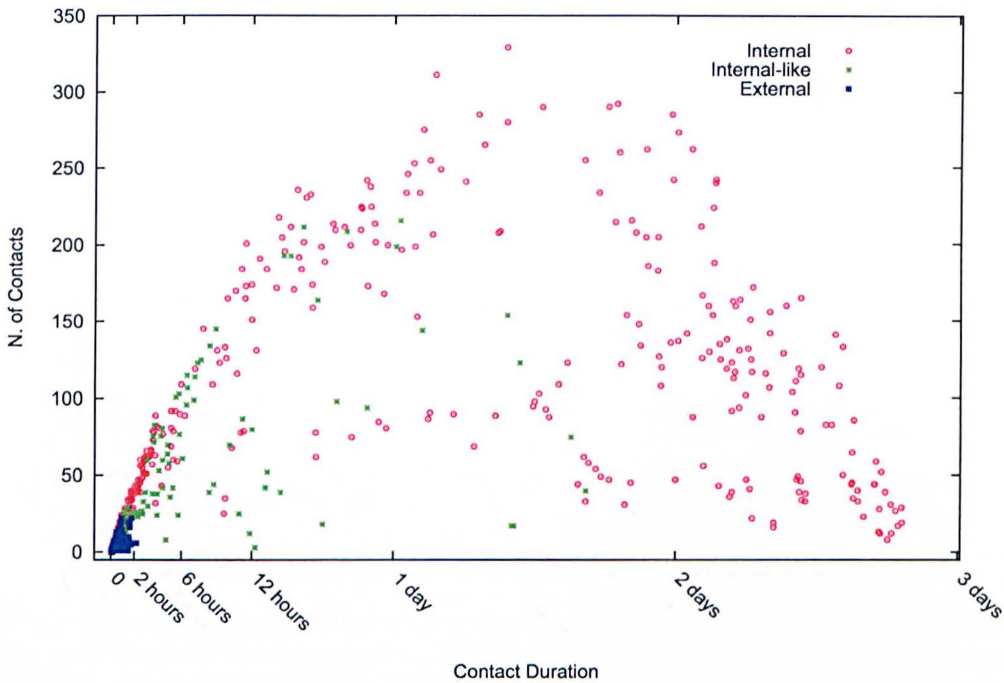

Figure 2.12: The number of contacts and contact durations of each device with all the internal devices

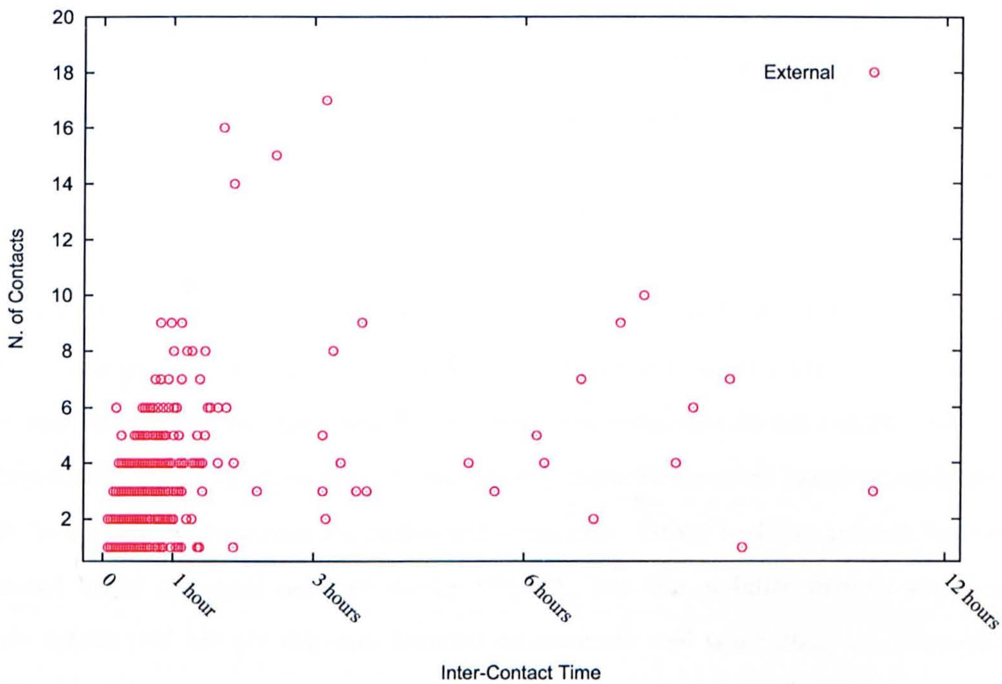

Figure 2.13: Number of contacts versus the inter-contact times for external devices

contacts with each external device, day by day, to filter external devices. In this next step we are only considering external devices in the left cluster of Figure 2.11 as we believe that a device with a long maximum inter-contact time is probably related to the environment. People rarely go back to the same shopping mall twice in a day and even less as the day passes. Consequently, in our mobility model, we do not consider customers/visitors involved in distinct multiple "visits". In Figure 2.13 we can see that 22 external devices out of 743 have a maximum inter-contact time longer than 3 hours (within a single day). The vast majority of these devices have inter-contact times lower than one hour. After three hours the frequency decreases drastically. We then classify external devices with inter-contact time smaller than three hours as likely to be carried by customers.

2.6 Studying Contacts among Nodes

The majority of work on ad hoc network research to date has been based on "unnatural" mobility models such as Random Walk Mobility Model and its derivatives [35]. Such mobility models seem to be unrealistic for everyday scenarios, and do not exhibit the kind of characteristics found in [1] or here. Consequently, network research based on such models must be considered unproven for real-world situations. Other mobility models have been proposed based on social network theory [37]-[39], but the mobility models which most closely reflect real life are the ones founded on accurate real trace data, i.e. trace-driven mobility models.

In this section we examine the data gathered to identify possible implications to consider in building forwarding algorithms as well as mobility models for network applications in shopping mall environments. The Figure 2.14 shows the distribution of the number of times each node was seen by one of the internal devices, distinguishing between internal and external nodes. Considering internal nodes, during the experiment, 14 of our smart phones were sighted between 340 and 1685 times, nine of our smart phones were sighted between 5 and 63 times, and one was sighted just once. These distributions suggest that different nodes have different contact relationships and that many of them (14 of the 25 smart phones) have good contact relationships. This might reflect an employees' mobility being mostly localized around the shop they work in, and sometimes moving away for scheduled and toilet breaks. The gap between the first and second group might suggest the difference between neighboring sellers and the rest of the sellers. Considering external nodes, the mode is 1 and the vast majority of external devices have less than 32 sightings, except for three of them which have between 169 and 224 sightings. But recall that "external" nodes could also be personal devices carried by sellers and/or shopping mall employees (i.e. safety guards, sweepers, stewards, etc.). From these results we can see significant differences between customers and shop employees. From this, we can argue that mobility models in which all the nodes have the same mobility patterns cannot adequately represent shopping mall environment.

The Figure 2.15 shows the number of times that pairs of (internal, internal) and (internal, external) nodes come in contact with each other. This distribution shows a considerable variability in the number of times pairs of smart phones saw each other. Unlike the results in [2], in our case pairs of internal nodes are uniformly spread along the number of contacts from 0 to the range (513-1024). This strengthens our conjecture that sellers, who are positioned within the shopping mall according to its structure and following a certain order (i.e. some are in charge of a specific area, others have particular tasks, etc.), have "duty-bound" mobility that links them to the shop where they are employed. The Figure 2.15 also suggests that sometime sellers move away from their working place to satisfy their needs. In contrast, in conference environments [2] most or all of the nodes are "free" to move without any boundaries. The plot also shows that the majority of pairs with external nodes have less than 16 contacts. Unlike internal pairs, the pattern of visibility with external devices does seem to reflect that in [2], for example, the number of pairs that never come into contact with each other is almost half of them. These results could not be reproduced by mobility models that give all nodes the same probability of meeting each other.

Figure 2.16 shows how many internal nodes saw a particular device over the whole six days (the plot does not tell us how many times the same device was seen). These two

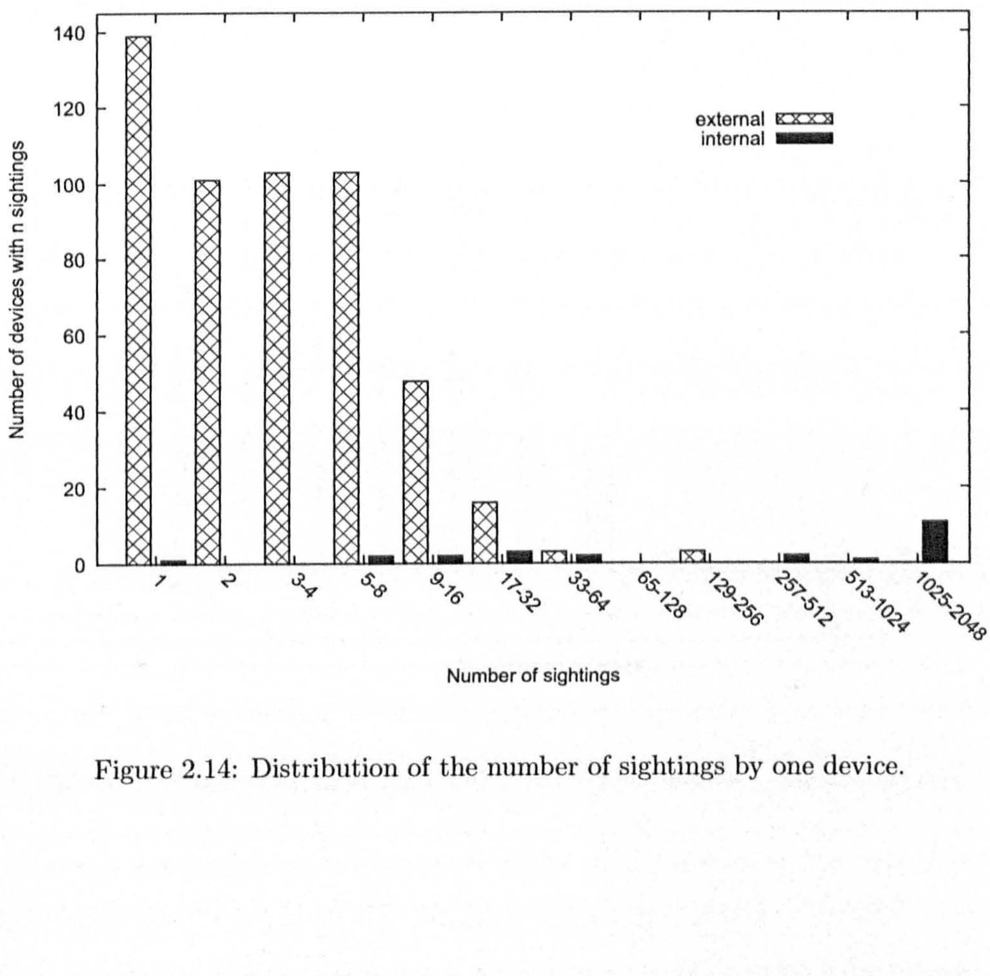

Figure 2.14: Distribution of the number of sightings by one device.

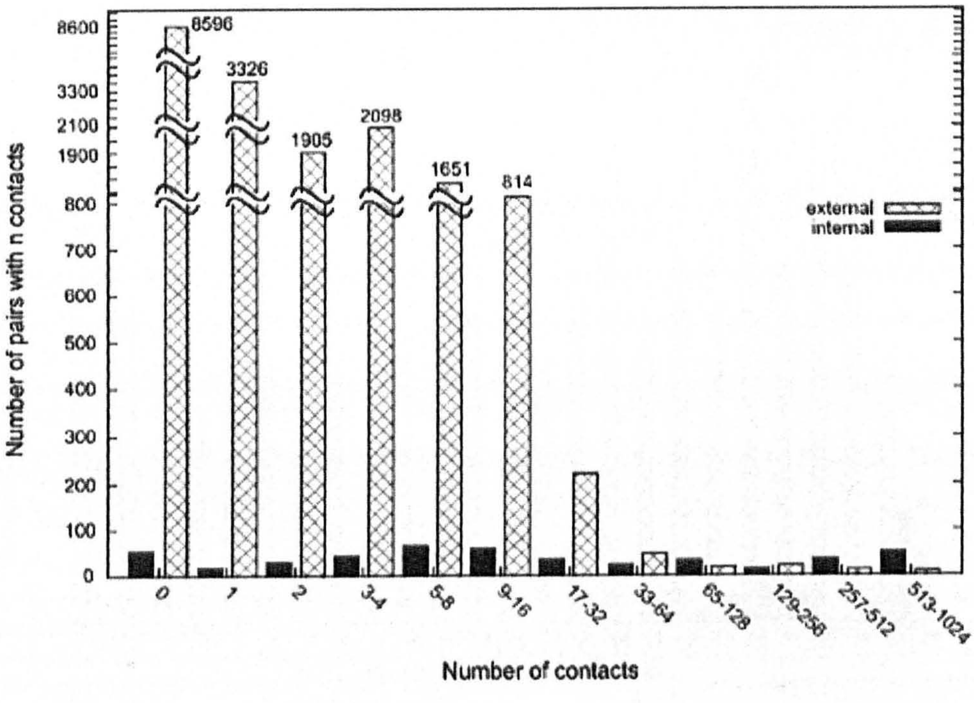

Figure 2.15: Distribution of the number of contacts between pairs of devices.

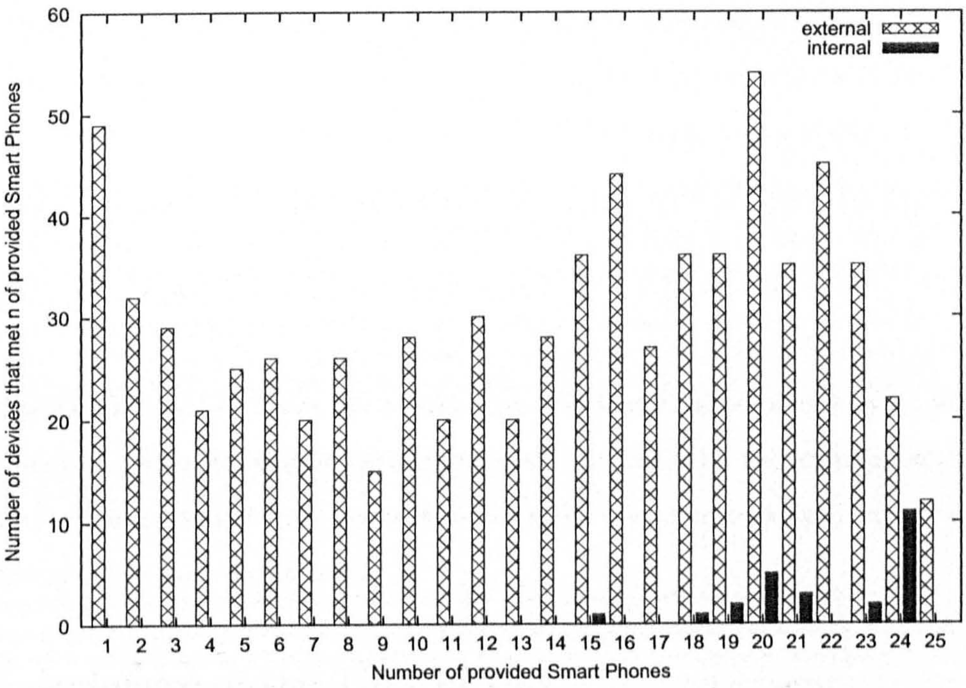

Figure 2.16: Distribution of the number of provided smart phones met by each device in the experiment.

distributions highlight the difference between internal and external nodes. Unlike the graph in [2] where iMotes carriers saw all but a few of the other iMotes and external devices were seen by only a couple of iMotes, here the majority of the customers meet more than half of the sellers, while almost all of the sellers meet at some point. We imagine that in a conference environment [2] the internal nodes are not always together; external devices could be seen by an internal device when distant from the conference and thus would be unlikely to be seen by any other internal device. But in shopping mall environments internal nodes are mainly duty-bound to the shop in which they are employed (during the day at least) moving away from time to time. Note also that six of the internal fixed nodes (out of seven) see between 20 and 24 other internal nodes. This suggests a possible role for fixed nodes to forward data contrary to the preference for mobile nodes in [72] (where the use of mobile nodes increases the capacity of the ad-hoc wireless networks). The analysis in [72] is based on the assumptions that all nodes are identical and uniformly visit the entire network area according to an ergodic mobility model based on independent and identically distributed trajectories. From our previous observations these assumptions do not hold for some real life scenarios such as shopping malls (in particular the assumption that the mobility of each node uniformly covers the entire space over time, making all nodes basically indistinguishable from each other).

2.7 Influence of the Time of Day

We now look briefly at distributions of contacts over the working day. Employees in the shopping mall where we ran the experiment work from 9am till 9pm. A few of them close the shop from 1pm till 3pm to take a break or tidy the merchandise. We split the working time into two intervals, from 9am to 3pm and from 3pm to 9pm, to see whether there were different contact distributions during the working day. Figure 2.17 shows the distributions of the inter-contact time for these six hour periods. It shows that the contact distribution has little or no visible time dependence during opening time of the shopping mall. As such, there is no evidence here for future forwarding algorithms for shopping mall environments to take into account temporal patterns.

2.8 Issues and Limitations

Gathering such a data set also presents many practical issues: dealing with deployment of mobile devices to a certain number of shopkeepers, the battery life of the devices, and minimizing the inconvenience of carrying the devices so that they are willing to do so at all times. I have been checking every day our smart phones to make sure that they were working properly and eventually charge the batteries during the night. Besides, in our investigation in the shopping mall, I could not provide customers with our smart phones for several practical reasons among which dealing with logistics management of distribution and retrieval, more devices to distribute and higher risk of theft. Therefore, our data set lacks contact traces from customers' personal devices to directly analyse inter-customers contacts.

There was nothing unusual in the shopping mall when I run this experiment, thus our smart phones have not recorded exceptional situations. This data capture took place in one shopping mall and during a regular week. Therefore, there is no guaranty that the results obtained from these traces are always reliable. In addition to that, our results are influenced by the granularity of the experiment, namely, for short event lengths, the data is affected by the granularity of measurement, that is 120 seconds. Bluetooth conflictions were taken into account as two or more devices in enquiry mode at the same time might not be able to answer to each other. Clock synchronization was also checked manually. All of the smart phones deployed in the shopping mall yielded useful logs and a valuable data set.

2.9 Summary

Bluetooth technology offers several opportunities, including interoperability, scalability, low cost, voice/data compatibility, the formation of ad-hoc networks and low power consump-

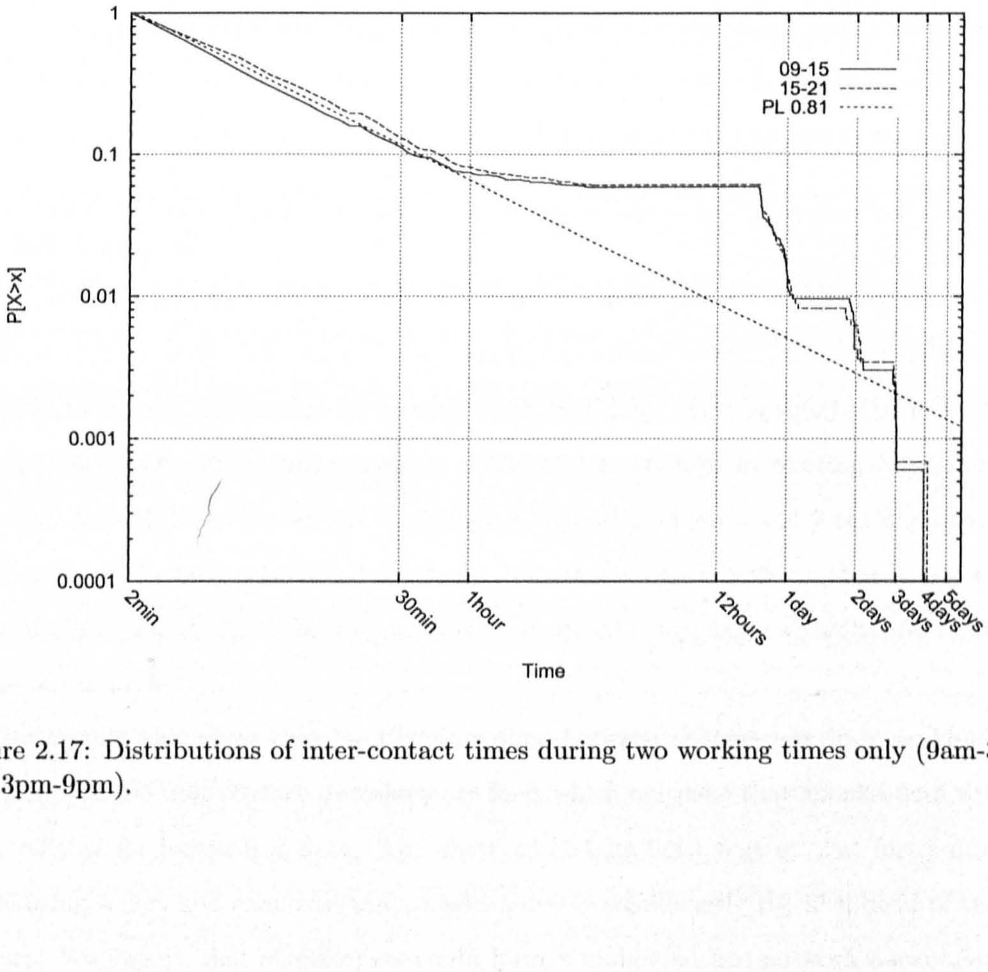

Figure 2.17: Distributions of inter-contact times during two working times only (9am-3pm and 3pm-9pm).

tion. Communication services that rely on this technology (and others like it) will strongly depend on human mobility characteristics.

In this chapter we have presented real-world measurement results from the mobility of people in a shopping mall environment. Although the distinction of classes of mobility in practical situations within shopping malls is somewhat obvious, we have presented evidence and some quantification of the ways in which they differ. These results are quite different from previous studies in a workplace [30], university campus [1, 31, 32, 33, 34] and conference scenarios [2], where power law coefficients approximate the inter-contact time distributions for longer periods of time. From our results, communication services might require specific networking protocols depending on the environment in which they are used. For a shopping mall network protocol we might seek to exploit the distinct mobility patterns of customers and shop employees.

We have identified groups of people who exhibit higher power law coefficients but only for short time periods. The neighboring shopkeepers distribution, labeled as neighboring internals in Figure 2.6, reveals a PL with coefficient 1.30. This is significant in that using multiple intermediate relays may be sufficient for stateless forwarding algorithms to converge. Indeed, if the power law coefficient is located between 1 and 2 the algorithm introduced by [72] would exhibit infinite delay. Nonetheless, [1] has shown that it is possible to build a forwarding algorithm that achieves a bounded delay, using a number of duplicate copies of the packet.

Our results also show that inter-contact time between shopkeepers in a working day is typically small and contact durations are long which suggests that shopkeepers will be more reliable for forwarding data. The observed distributions suggest that forwarding to neighboring sellers and shop assistants might increase significantly the likelihood of timely contact. We believe that shopkeepers could form a mobile ad-hoc network backbone and the starting point from which to build wider networks in shopping mall environments. The identification of such groups of people could help greatly in forwarding data.

We have also shown that people's motion is different according to their relationship to the environment they are in. We provided a method based on contact duration, inter-contact time and frequency to distinguish two groups of people, visitors/customers and shopping mall related people, with different mobility patterns.

We have explored various characteristics of the collected data, from the sellers' point of view, which might be used to design improved forwarding algorithms. Firstly, when forwarding to neighboring shopkeepers the power law coefficient is more than 1; identifying neighboring shopkeepers would be a great help in forwarding data between two shop employees. Secondly, we observed that nodes do not behave the same; for example, sellers and some "customers" are much more active and see each other more often than others. Thirdly, we observed that forwarding algorithms do not appear to need to take into account broad temporal patterns in this environment. In the next chapter we present our scenario generation tool and the shopping mall mobility model which aim to represent salient aspect of the observed human mobility patterns. Indeed, the measurements we have presented here are used in Chapter 4 to validate our mobility model.

Chapter 3

A Mobility Scenario Generation Tool for "Structured" Environments

Simplicity is prerequisite for reliability.

Edsger Dijkstra

In this chapter we present a new mobility model generation tool and propose a realistic mobility model for shopping mall environments based on measurements and statistical analysis of individuals' localization from real traces collected in such environments (as described in Chapter 2). Our mobility trace generator supports five mobility models: the Shopping Mall mobility model, the basic Random Walk mobility model, the Random Way-Point mobility model and variations of these for shopping mall-like environments with inter-arrival time.

We present our shopping mall mobility model along with its distinct dynamics for customers and sellers in Section 3.3. The new mobility model is implemented by our mobility model generation tool which is described in Section 3.4. Finally, the last section of this chapter explains how we determined the cumulative distribution functions which are needed by our tool to simulate a mobility model. In Chapter 4 we evaluate and validate our mobility model with respect to real contact traces.

3.1 Background

Even though real traces identifying user mobility would be preferable for evaluating the characteristics of mobile ad hoc network protocols, it is very difficult to trace node movement in real large-scale mobile environments. Although random movement models generate traces that do not reflect real world observations (as discussed in Section 2.1), synthetic traces are very often used when simulating mobile networks. That is due to many reasons. First, even though there is a repository of public available wireless traces (CRAWDAD [1] [59]), the number of available real traces in the public domain is limited and covers a number of specific scenarios. Also, real traces do not provide information such as the distribution of the speed or the density of the hosts, which prevents sensitivity analysis. Moreover, sometimes it may be more useful to have a mathematical model that describes the movement of the nodes in a simulation in order to consider its impact on the design of protocols and applications.

Furthermore, simulations allow us to model things that could not be captured in field trials. For example, in our investigation in the shopping mall (see Section 2.3) customers were not provided with devices for practical reasons (i.e. numbers of devices, logistics of distribution and retrieval, risk of theft). Thus, we could not log contacts from customers' perspective, in particular contacts between customers. Our shopping mall mobility model allows us to simulate the same field trial conducted in the real shopping mall and to calculate

[1] Currently (May 2009): 1645 users from 851 institutions in 63 countries, 213 contributors, 55 data sets, 20 tools, 237 papers. Mirror sites: http://uk.CRAWDAD.org (UK) and http://au.CRAWDAD.org (AU)

contact opportunities from the customer's point of view. This relies on approximating the customers' mobility from the observed data and modeling it.

Designing realistic mobility models is one of the most critical and difficult aspects of the simulation of protocols and applications in mobile environments. In general, an individual's mobility is characterized by a distinct mobility pattern and can be described by a distinct algorithm. People's mobility can be clustered based on several factors which are strongly related to the environment in which they are. In our mobility model we could have clustered individuals by distinguishing for example between adults and teenagers, or between males and females. For instance, it is widely held that the mobility patterns of men and women in shopping centres are distinct; Figure 3.1 is self-explanatory. :-) From the analysis of our data set in Chapter 2 we have seen that people behave in different ways. However, we wanted to keep mobility pattern distinctions as simple as possible and chose to differentiate between two groups, customers and sellers, which in turn, have different mobility patterns.

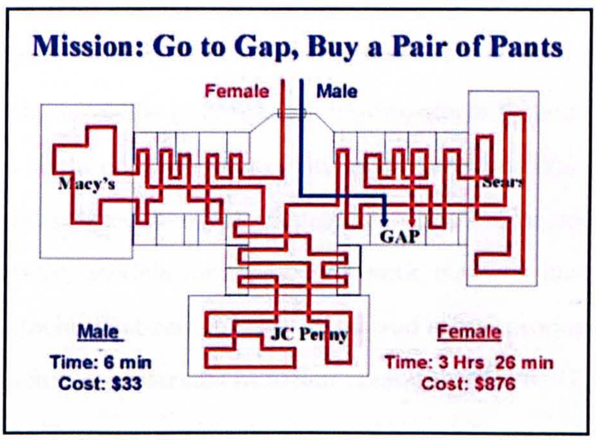

Figure 3.1: Men and Women: different mobility patterns (from the correspondence of a friend... a woman! ;-))

Based on this grouping we propose a mobility model based on measured mobility characteristics. These characteristics are expressed as cumulative distribution functions which capture the mobility characteristics of sellers and customers in a shopping mall.

We conduct statistical analysis on our data set (described in Section 3.5). The data traces collected by our smart phones contain enough implicit location information to train a mobility model for network simulations. By exploiting fixed nodes (motionless smart phones left by the tills) in our experiment we were able to see when clerks and shop assistants were in their working place or somewhere else, and how much time customers spent in a shop and in the mall. For this, we considered seven out of the eight fixed phones because the Bluetooth connectivity range of these smart phones could cover the entire surface of the respective shop. The empirical distributions were thus fitted to theoretical probability distributions described in Section 3.5.

3.2 Related Work

3.2.1 Synthetic Mobility Models

In the past, many synthetic mobility models have been adopted (see [35] for a survey of them) to run simulations. Among them, the Random Walk mobility model, equivalent to Brownian motion which represents pure random movements of the entities of a system [73], is the simplest model. A slight enhancement of this is the Random Way-Point mobility model in which pauses are introduced between changes in direction or speed. A large number of other artificial mobility models for ad hoc network research have been presented, for example assuming obstacles that restrict movement and signal propagation and focusing on particular scenarios such as pedestrians in urban areas [74, 75, 76, 77], vehicular traffic [78] and disaster areas [79]. However, synthetic movement models are not very reliable because they are based on random mechanisms which show properties (such as the duration of the contacts between the mobile nodes and the inter-contacts time) very different from those extracted from real scenarios. This analysis is confirmed by the examination of the available real traces [1, 2, 29, 30, 31, 32, 33, 34, 80].

Other mobility models have been proposed based on social network theory. In [40]

Herrmann introduced a social mobility model for mobile ad hoc networks to study the effects of social networking among mobile users, but it allows the definition of pairwise relationships only. Musolesi et al. [37, 38] proposed a community based mobility model based on the needs of humans to socialize. Mobile devices are commonly carried by humans, so the movement of such devices is necessarily based on human decisions and socialization behaviour. This mobility model allows the definition of a complete "Interaction Matrix" between all of the people. But this approach is highly complex and it is not suitable to define groups of people expressing different mobility patterns. In this model the social attraction level is determinate by how many "friends" are in the same square. Actually, meeting people depends on the environment in which they are and the time of day. Besides, node movements in such a model are relatively homogeneous. Venkateswaran et al. [39] provided a theoretical framework for a mobility model based on social network theory. They capture the preferences in choosing destinations of pedestrian mobility pattern in presence of obstacles on the basis of social factors. Contrary to Musolesi et al. [37, 38], they do not consider a matrix to represent the interaction between two individuals but express it as a function of time, network parameters and social issues. Theoretical models have been also developed to reproduce the properties of these networks, such as the so-called small worlds model proposed by Watts and Strogatz [81] or various scale-free models [82, 83].

In the Time-Variant mobility model presented by Hsu et al. [44] nodes move to different squares at different times of day in a periodic manner and their movement is homogeneous, that is every node follows the same instructions.

Rhee et al. [41] presented a mobility model which generates movement traces based on Levy Walk[2]. They statistically establish that the mobility patterns of humans mobility at outdoor settings within a scale of less than 10 km strongly resemble Levy walks with power law distribution. This model produces inter-contact time and contact duration distributions similar to real world traces. However, in mobility models based on Levy Walks and entity mobility models [35] all of the nodes move independently all of the time. Therefore, such

[2]The Levy Walk mobility model is a derivative of the Random Walk mobility model in which the step-lengths are distributed according to a heavy-tailed probability distribution.

models do not generate any social structure between the nodes. Movements in shopping mall environments have such an independent component, for example going to grocery shops rather than to the pharmacy, but many movements end up with meetings of friends (customers) or gatherings of people for example in cafés (customers and sellers). In such an environment, it is the shop with its merchandise and offered services that attracts people; some shops can have higher attraction to customers and sellers than others. Besides, sellers are most of the time duty bounded to their workplace.

Piórkowski et al. [84] proposed a macroscopic mobility model for clustered networks called Heterogeneous Random Walk. It offers an elegant balance between capturing mobility characteristics observed at macroscopic level in the real-life settings and the mathematical simplicity. They also provided a closed-form expression of the time-stationary distribution of node position.

Lee et al. [85] presented a new mobility model called SLAW (Self-similar Least Action Walk) that captures the effect of human mobility patterns found in real human mobility traces. This mobility model can produce synthetic walk traces containing significant statistical patterns of human mobility similar to those derived from real traces, namely truncated power-law distributions of flights, pause-times and inter-contact times, fractal way-points, and heterogeneously defined areas of individual mobility.

In a recent work Mei et al. [45, 46] presented a simple mobility model that generates small worlds, SWIM (Small World In Motion). This model is based on the simple assumption that people go more often to places not very far from their home and where they can meet a lot of other people. Each node is assigned a randomly and uniformly chosen point over the network area, called home. Then, the node itself assigns to each possible destination a weight that grows with the popularity of the place and decreases with the distance from home. The weight represents the probability for the node to choose that place as its next destination. We believe that this approach is not always valid in shopping mall environments. In such scenarios people mainly choose their destination driven by their needs, mostly related to their purchase. Our model allows shops with different attraction levels for both customers and sellers. We believe that some shops attract more customers than others based on their merchandise. A different approach might be to consider the number of sellers of each shop as attraction level, as the number of sellers is somehow related to the number of customers that they assist.

Little work has been made on indoor movement. Our mobility model and those proposed by Ekman et al. [42] and Minder et al. [43] are some of the models made on indoor movement. However, [42] combines indoor and outdoor movements. Nonetheless, [42], as well as [43], supports only one class of individuals (common working people), while our model considers two classes of people, customers and sellers, with different mobility patterns, which take place at the same time. One of the biggest issues with most of the synthetic models is that they are not capturing heterogeneous behaviour of nodes. Instead, our Shopping Mall mobility model is heterogeneous in both time and space, and captures several different mobility characteristics at a lower level of abstraction than many other previous models.

In [35] Camp et al. also describes group mobility models which focus on moving an entire group but not on the formation process of a group. Some previous mobility models [84, 42, 43] support group mobility and their formation. Our model does not support group mobility while the number of people gathering in shops varies widely. Additionally, the structure of organizations has to be considered in the model. Our model supports two groups of individuals with different mobility patterns. Sellers meet with each other and are in contact with neighbouring sellers longer than with customers.

In [42] Ekman et al. presented a new movement model to be used in DTN simulations, called the Working Day Movement Model, which intuitively depicts the movement pattern of people. The model presents the everyday life of average people that go to their workplace in the morning, spend their day at work, and commute back to their homes at evenings. They combined different movement model elements (called *submodels*) together to build the whole scenario; each submodel describes a distinct activity. These submodules repeat every day. Their parametrisation and adding further submodels as needed allows fine-tuning the model to meet the needs of the target scenarios. Their mobility model tries to capture several mobility characteristics at a lower level than many other models. The mobility model presented in this thesis is part of this effort. We have decided to narrow down the playground scenario to structure environments, with particular regard to shopping malls. Our shopping mall scenario might be a submodule of a bigger scenario. The approach of this model is similar to our Shopping Mall mobility model. In our model, parameterised submodels of two distinct groups of people result in periodic movements.

In the Working Day movement model a temporal structure dictates the activities of individuals. They used some distribution functions, observed from earlier research in office environments [43] and from general movements inside buildings [41], that assign time to all the activities. Similar work was conducted by Minder et al. [43] who set up an experiment to record the movement and meeting patterns of employees in their department in order to derive information about the duration and composition of meetings. This data was used in the creation of a meeting-based movement model. The same approach is used for our Shopping Mall mobility model. We have conducted an experiment to gather data about contacts between devices carried by humans in a shopping mall in order to derive information about mobility characteristics in such an environment. Our model also considers the distributions for the customers' inter-arrival time and their staying in the mall which makes the number of nodes in the simulation area varying with time.

Like in [42, 44, 43] also in our Shopping Mall mobility model communities and social relationships are formed when a set of nodes are doing the same activity in the same shop. For example, sellers within the same workplace are colleagues, while customers in the same shop or café might be friends or strangers with each other.

3.2.2 Models Based on Pedestrian Shopping Behaviour

Pedestrian movement is a significant subject to many domains of interest. Modelling of pedestrian destination choice has been dominantly based on disaggregate discrete choice models of increasing complexity [86, 87]. These models take a decision by considering a potentially large set of influencing factors. However, the large variety of temporal, spatial and personal factors which exert influence over destination choice may make it impossible to capture the essence of choice under all circumstances. Therefore, the wisdom of choosing a particular approach can only be judged by reference to the specific purpose of the chosen model.

In particular, pedestrian movement has been significant in considering placement of anchor stores [88] and the design of shopping environments [89]. Barnard [90] provides a review of basic multinomial logit models of shopping destination choice and some of their extensions. Borgers et al. [91, 92] present a model to simulate individual route choice behaviour of pedestrians in downtown shopping areas whose scenarios might be similar to shopping malls. They assume that pedestrians enter the downtown shopping area at entry points; after that, they repeatedly choose one of the connecting links to move onwards; when the trip finishes they exit the downtown area from where they entered. The model employs an endogenous utility function to drive the choice of a link which is based on some variables describing characteristics like the supply of shops, distance, and history of the trip. The data to estimate the parameters of the model and evaluate it was collected for two days by interviewers positioned at the exit points of the downtown shopping areas of two Dutch cities, Eindhoven and Maastricht.

Zhu et al. [93] proposed a modelling framework for pedestrian shopping behaviour incorporating principles of bounded rationality. They extend the classical deterministic forms of disaggregate discrete choice models by incorporating threshold heterogeneity and derive probability forms. They also contend cyclical decisions to predict spatio-temporal pedestrian behaviour: *go-home*, which refers to a pedestrian deciding whether or not to end the shopping trip and leave the shopping area; *direction choice decision*, if he decides not to go-home and chooses a walking direction; *rest decision*, to make a rest when tired of walking or shopping; *store patronage decision*, if the pedestrian decides not to take a rest and to look for a shop to visit. The proposed models are implemented using data on pedestrian behaviour in Wang Fujing Street, the city centre of Beijing, China.

Kitazawa et al. [94] introduce a study of pedestrian behaviour modelling which incorporates ideas about agent-based systems and the traffic models based on the utility-maximization theory. They implement a simulation model using the shortest-path model as one of the evaluation criteria of Genetic Algorithms to computationally emulate retail movements of shoppers in a shopping centre and to test the accuracy of the model by comparison between the routes estimated by the model and actual trajectories of shoppers. A two-day survey on retail behaviour of shoppers was undertaken at a large shopping centre in Tokyo, Japan. Besides, eighteen students were asked to shop for two hours and the routes they took were tracked and recorded. Digital video cameras were used as main sensors of the measurement systems in this study. Every 30 seconds, the individual who is closest to the camera's location was identified and video images and recorded.

To some extent, the above-mentioned approaches are slightly similar to our Shopping Mall model. In fact, they all consider a simulation area, an entry and exit point, and shoppers cyclically repeat some steps before leaving (see Section 3.3). However, they all differ from our Shopping Mall mobility model because their shopper destination choice is based on utility functions while in our mobility model shoppers randomly choose a destination. Besides, they only model shopper movement, whereas in ours seller movement is also considered. Moreover, they collected data to implement and evaluate their models by means of personal interviews at certain locations of a shopping area. In their investigations they were collecting information about pedestrian shopping behaviour. Consequently, this will model shoppers' mobility. Instead, we collected just contact data between individuals by exploiting handheld wireless devices with the main purpose to capture people's mobility. Kitazawa et al. [94] tried to use technology by employing fixed cameras as sensors to detect people in sight. However, unlike wireless devices which can sense other in range wireless devices from all directions, cameras can only record people within a certain angle even though they do not carry any wireless device.

3.3 Shopping Mall Mobility Model

A mobility model is a set of rules used to generate trajectories for mobile entities. In particular, mobility models used for network simulations generate network topology changes due to node movement. A network simulator must know the position of a mobile node at each moment. Using the exact node position the simulator can compute signal fading from one node to another and take actions based on the current network topology (e.g., determine the set of nodes that will receive a certain packet).

Our mobility model has been designed to model the movement of individuals in a shopping mall, but it can be used to reproduce scenarios in other settings which can be described by a 2D plan, i.e. urban areas, megastructures, settlements, built complexes, museums, trade fairs, music festivals, stadiums, etc. This model considers the structure of the environment and some mobility characteristics which are intrinsic to the scenario taken into account, i.e. time of arrival to and departure from the "playground", permanence of premises, shops, walls, obstacles, etc. The internal structure is significant in that people in shopping malls, as well as in places like university campuses and conferences, often move by selecting a specific destination and following a well-defined path to reach their destination. The selection of the direction is influenced by both pathways and obstacles. In particular, in shopping malls individuals walk from one shop to any other, or from one location to another, following corridors, pathways, galleries, etc. A node's mobility is affected by the surrounding physical world, in particular, simulated humans must not walk trough walls.

In Section 2.5, by analysing shopping mall mobility patterns we identified two distinct populations, that we label as customers and sellers, and that have two different mobility models. The number of sellers is initially defined by the user as an input to the model (see Section 3.4.3). The number of customers depends on the frequency with which they arrive at the mall. The customers interarrival time and their stay respectively in a shop and in the mall, and how long sellers use to stay in and out of their working place are all inputs to the model.

In the next two sections we describe respectively customers' and sellers' dynamics. They all move from one shop to another in the mall by choosing the shortest path. The entire shopping centre can be seen as a graph where the entrances, mall interceptions, shops and stores are the vertexes, and the corridors, streets and galleries are the edges.

3.3.1 Customers' Dynamics

The simulated population of customers arrives at the mall according to random sampling of an interarrival time distribution.

Once in the mall, customers randomly choose a shop/store to go to and spend some time in. Inside the shop they follow a Random Way-Point model [95]. This model is widely used [96, 97, 98, 99] and includes pause times between changes in direction and/or speed. The time spent in each shop and in the entire mall is derived from a random sampling of the corresponding cumulative distribution functions that are provided to the model (see Section 3.5). When the time they are allowed to spend in a shop expires they randomly choose a new shop to go to and cyclically repeat the above steps.

Group relationships have not been considered; customers individually wander within the mall. When the time they are allowed to spend in the mall expires, they leave via the closest exit.

Our scenario generator provides a some flexibility in the selection of the target shop by allowing a distinct attraction level for customers and sellers to be assigned to each location. For our scenario, we assume that all the shops have the same attraction level equal to 1, both for customers and sellers. Thus, customers may go back and forth within the shopping mall depending on successive random choices. This behaviour is acceptable for relatively small environments such as our shopping mall but it is probably not suitable for very large environments.

3.3.2 Sellers' Dynamics

Sellers are initially positioned in their "own" working place. Then, after a certain random time sampled from the relevant cumulative distribution function, they randomly choose a place in the mall to go and spend some time again dictated by a specific probability distribution function (see Section 3.5). When the time assigned for staying out expires they go back to their working place by the shortest path and cyclically repeat the above steps.

As mentioned above, the attraction level of each shop for sellers is 1. Thus, sellers have the same probability of choosing one shop rather than another during a "break". As for customers, this behaviour may not be suitable for large environments even though it may be acceptable for a small environment such as our shopping mall.

Like customers, sellers follow a Random Way-Point model when inside a shop. Also group relationships are not modelled with each seller moving independently.

3.4 Mobility Model Generation Tool

We have developed a tool that implements the Shopping Mall mobility model and a number of other mobility models. Our mobility scenario generation tool is a Java application. For a supported mobility model it requires input parameters appropriate to the model and outputs a list of node trajectories. We begin by describing the tool as a whole before describing in more detail each supported mobility model.

To design a mobility model we have considered two components: a spatial component and a temporal component. The spatial component describes where the mobile entity is moving, and the temporal component describes when an entity is moving and at which speed. Details of the implementation of our software tool are in the Appendix C.

3.4.1 Features Overview

Our Java software tool provides certain features to the user to model and analyse mobility in structured environments. This mobility model generation tool is available to other research groups upon request. The main features of the software developed are the following:

- It creates a shopping mall scenario and allows further mobility models to be easily hooked.

- The plan structure can be described without programming requirements (see Figure 3.4).
- Fine-grained movement traces for shopping mall scenarios as well as for other different structured environments can be generated.
- The generated mobility traces are compatible with the Omnet++ simulator [53], one of the most popular discrete event network simulation framework in the mobile ad hoc network research community.
- Mobility traces for some traditional random mobility models can also be produced.
- Easy to use: starting the program without or with incomplete command line parameters prints a detailed help message (see Section 3.4.2).

This software has been tested with Java 1.5.0_11 and 1.6.0_15.

3.4.2 Requirements and Design

The syntax of the command line and the design of our scenario generator roughly follow the structure of Bonnmotion [100], a tool developed within the Communication Systems group at the Institute of Computer Science 4 of the University of Bonn, in Germany, that creates and analyses mobility scenarios for the investigation of mobile ad hoc network characteristics.

External Libraries

Our mobility model generator also depends on *SSJ*, a Java library for stochastic simulation developed in the Département d'Informatique et de Recherche Opérationnelle (DIRO), at the Université de Montréal [101], and *Apache Commons Mathematics*, a library of mathematics and statistics components [102].

Usage

Currently, five mobility models can be generated, the Shopping Mall mobility model, the typical Random Walk and Random Way-Point mobility models as well as their derivatives with interarrival time (they are introduced in Section 3.4.3). In this thesis we focus on a shopping mall scenario but mobility scenarios like university campus, trade fair, music festival, automobile race track, stadium, can also be reproduced in the same way.

The application starts through the command "MM". The syntax is the following:

```
MM <output file>  <application>  <plan>  <application parameters>
```

`<application>` identifies one of the three configurations we have implemented to generate our above-mentioned mobility models. The mobility model generator takes as input an `svg` file `<plan>`, which provides the entire shopping mall plan and the cumulative distribution functions. SVG (Scalable Vector Graphic [103]) is a language for describing two-dimensional graphics and graphical applications in XML. It also takes `<application parameters>` on the command line which define simulation time, speed range and pause time of the nodes involved. Important parameters which could be also used with all the models are the following: the random seed with `-R`, which can be optional as it can be automatically chosen, the maximum and minimum speed in metres per second respectively with `-h` and `-l` and pause time with `-p`, the scenario duration (in seconds) with `-d` and the `-i` parameter specifying how many additional seconds at the beginning of the scenario should be skipped. Initially, -i has a high default value (1 hour) as it has been observed that with the Random Waypoint model [104, 105], nodes have a higher probability of being near the center of the simulation area, while they are initially uniformly distributed over the simulation area. In our scenario, the Random Waypoint model is used to simulate the mobility of sellers and customers in shops and stores. The movement traces must be saved into a file by means of the option "`-f <output file>`. The scenario is saved in two files: one with the suffix ".params" containing the complete set of parameters used for the simulation, and the second with the suffix ".movements.gz" containing the movement data (gzipped).

3.4.3 Supported Mobility Models

As mentioned in the Section 3.3, to define the environment that we would like to reproduce, which is made of boundaries, obstacles, walls, paths, mall intersections and restrictions of the simulated world we have used an SVG application. SVG is a language for describing two-dimensional graphics and graphical applications in XML. The SVG specification is an open standard that has been under development by the World Wide Web Consortium (W3C). SVG images can be created and edited with any text editor, but specialized SVG-based drawing programs are also available. We have used Inkscape [106], an open source SVG graphics editor released under the GNU GPL, to draw the scenarios for our simulations. In Figure 3.4 straight lines and polygons represent obstacles and shops while black and red dots respectively identify mobile and fixed nodes.

In addition, our scenario generation tool requires more parameters to build the simulated world: the simulation time, the random seed, the higher and lower speed of the nodes, and pause between two successive movements. These parameter values are used by the mobility model generation tool to generate different mobility scenarios. Our tool provides three configurations, the `SimplestRWP`, the `RandomWayPoint` and the `MallMotion`, which are described in the next sections, to generate five mobility models.

Configurations

1. `SimplestRWP`: This configuration can generate the typical Random Way-Point as well as the Random Walk mobility model [35]. The Random Way-Point Model was first proposed by Johnson and Maltz [107]. Because of their simplicity, they became soon 'benchmark' mobility models to evaluate MANET routing protocols. The Random Way-Point mobility model is a derivative of the Random Walk model. It is based on

random directions and speeds like the Random Walk, but it also includes pause times between changes in destination and speed.

`SimplestRWP` reproduces these two traditional models within a certain area. The generation of a Random Walk rather than a Random Way-Point mobility model depends on the parameter `-p`, which indicates the maximum pause time. If `-p = 0` this will result in a Random Walk model. The following example command line generates a Random Walk mobility model (`-p = 0`). The mobility traces generated by this command line have been used for our simulation study as well.

```
MM -f scenario SimplestRWP Simplest.svg -d 43200 -i 3600 -h 1.65 \
                                           -l 1.65 -p 0   (3.1)
```

The command line 3.1 creates Random Walk scenario lasting 12 hours, i.e. -d 43200 (a working day), cutting off an initial phase of 3600 seconds. The `-i` parameter specifies, how many additional seconds at the beginning of the scenario should be skipped. Each node moves with a constant speed of $1.65m/s$. The `Simplest.svg` used in the command line 3.1, which identifies the plan of the playground, is shown in Figure 3.2.

As you can see in Figure 3.2, the `SimplestRWP` configuration does not require any probability distribution functions. In fact, the only nodes in play are the ones drawn on the svg plan, i.e. the black dots. This means that in this mobility model the number of nodes is constant. Black dots identify mobile nodes while red dots reproduce motionless nodes. The `SimplestRWP` class reference and UML diagram is in the Appendix D.5.

2. `RandomWayPoint`: As above mentioned, the Random Way-Point is a simple mobility model based on random direction, speeds and pauses. The Random Way-Point model

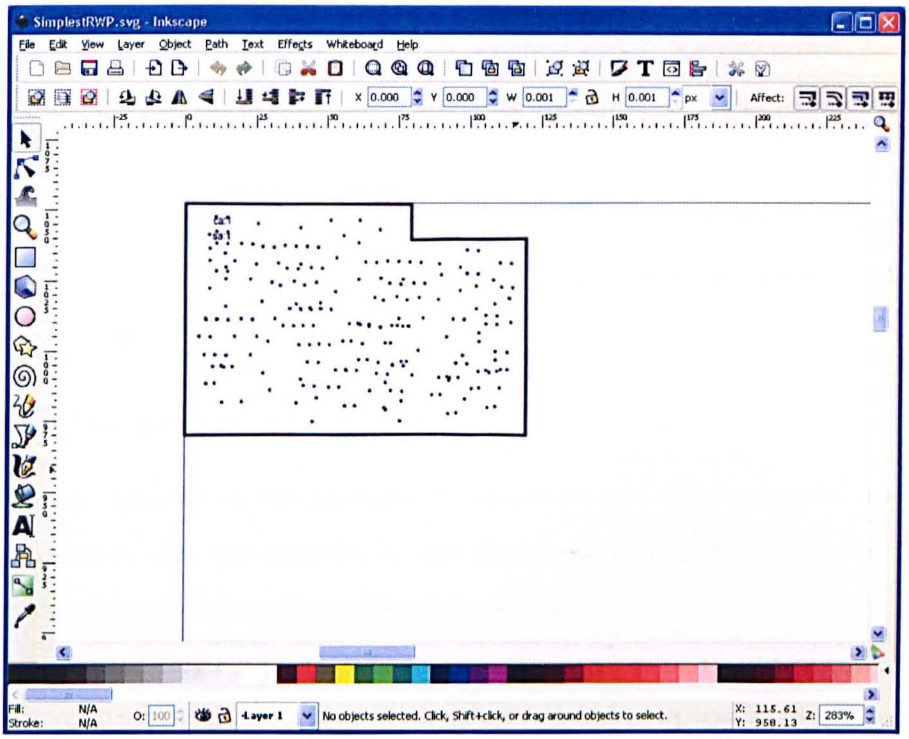

Figure 3.2: Plan and settings for the `SimplestRWP` configuration drawn using Inkscape (SimplestRWP.svg)

is widely used in simulations of mobile networks [96, 97, 98, 99]. This configuration supports a variation of the classical Random Way-Point and Random Walk models in which nodes enter and leave the playground over time. Specifically, nodes arrive at specific points of the playground with a certain frequency; after that, they follow a Random Walk or Random Way-Point mobility model; and finally, when their time expires, they move to the closest exit and get out of the playground. In this way, the specific nodes involved in the scenario varies with the time although the number is reasonably constant over time. As for the previous models, the generation of a Random Walk mobility model rather than a Random Way-Point mobility model depends on the `-p` pause parameter.

To generate the Random Walk and the Random Way-Point mobility models we need to provide the scenario generator with the following cumulative distribution functions:

- the time spent by nodes in the playground,
- and the nodes' inter-arrival time.

These are provided to the generator by annotations of the drawing in the svg file. The nodes in play can move freely over the whole area of the playground as walls, corridors and obstacles are not taken into account.

Figure 3.3 presents the plan and settings saved in svg format and handed to our scenario generator. For our simulation study we consider as playground the same surface and external boundaries as the shopping mall in Figure 3.4. The **`RandomWayPoint`** class reference and UML diagram is in the Appendix D.4.

An example of command line, which is the one we used to generate a Random Walk mobility model with inter-arrival time for our simulation study, is as follows:

```
MM -f scenario RandomWayPoint RWP.svg -d 43200 -i 3600 -h 1.65 \
                                          -l 1.65 -p 0
```
(3.2)

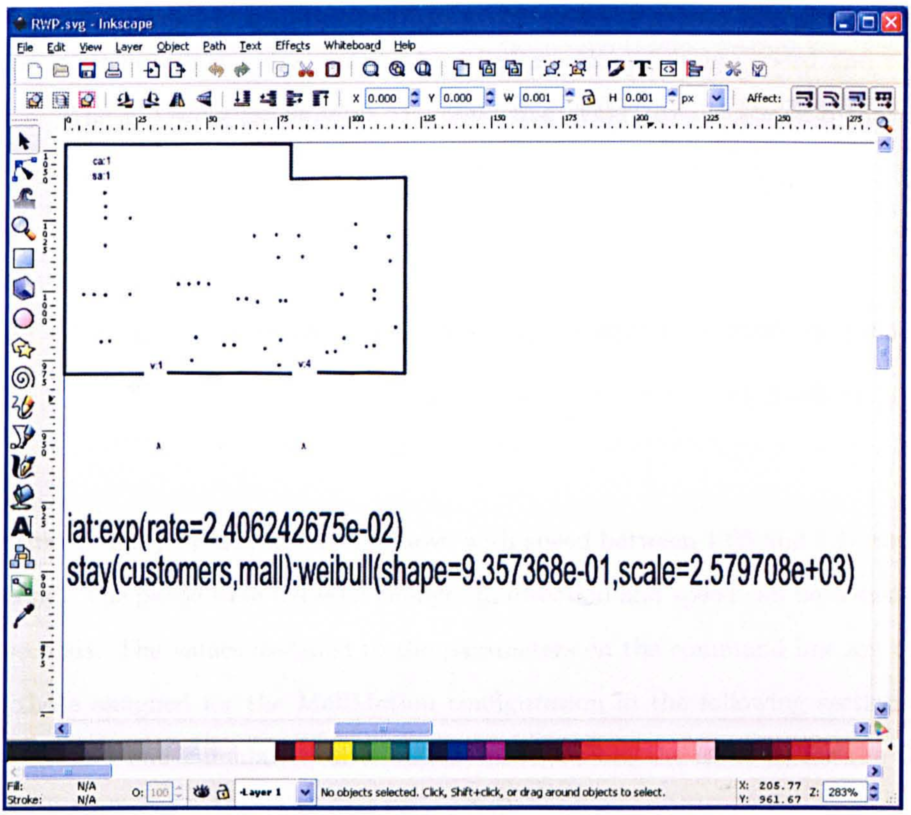

Figure 3.3: Plan and settings for the `RandomWayPoint` configuration drawn using Inkscape (RWP.svg)

The duration is 12 hours, i.e. -d 43200. `RWP.svg`, handing in plan of the playground and cumulative distribution functions to the scenario generator, is shown in Figure 3.3. The maximum and minimum speed are the same which means that nodes will move with constant speed of 1.65 metres per second. The pause between changes of direction is 0.

The command line to generate a Random Way-Point mobility model with inter-arrival time is similar to the above example except for the minimum speed and the pause time. The following example of command line generates the scenario that we take into account for our simulation study:

```
MM -f scenario RandomWayPoint RWP.svg -d 43200 -i 3600 -h 1.65 \
                                            -l 1.15 -p 2
```

(3.3)

In this mobility model, nodes can move with speed between 1.65 and 1.15 metres per second. The pause time between changes in direction and speed can be between 0 and 2 seconds. The values assigned to the parameters on the command line are the same as those assigned for the MallMotion configuration in the following section 3. The playground and cumulative distribution functions are the same as for the Random Walk with inter-arrival time (see Figure 3.3).

3. `MallMotion`: This configuration is able to model structured scenarios and in particular our mall motion model as introduced in Section 3.3. The configuration for this model consists of several components. The first component is the playground in which shapes and sizes of the structures, such as rooms, buildings, pathways or obstacles, are defined and sellers are placed (see Figure 3.4 and appendix E.1 for the textual mode). The sellers are identified by black dots, initially positioned in their working place. The red squares dots identify fixed nodes. They are meant to correspond to the smart

phones that were placed in some shops in the mall study. Our model can handle any arbitrary shapes and positions of structures [3] which allow us to model a wide variety of real-world topographies. We were very precise in drawing the shopping mall as we have its original plan. We followed the same scale considered in the Figure 2.1 which shows the architect's plan of the shopping mall where we run our experiment to collect Bluetooth contact data.

The second component of our mobility model is the movement backbone which is a graph representing the pathways along which mobile nodes move to go from one place to the other. Mall common spaces, intersections and entrances are respectively identified by "$V : [1..n]$" and "$\wedge$". These guide nodes through the mall. We model people moving from one location to another in the mall by choosing the shortest path along this movement backbone. To accomplish this we used the Dijkstra's algorithm on a graph where the mall interceptions, shops and stores are the nodes, and the corridors, streets and galleries are the edges.

The third component of the model is the destination selection. We assign customers and sellers' attraction levels (i.e. `ca:` "customers attraction level" and `sa:` "sellers attraction level" followed by an integer number) to each room of the mall that would influence the choice of individuals in going to one shop rather than another; higher values being the more attractive.

Finally, the fourth component is a set of cumulative distribution functions that dictate how nodes move within the shopping mall. These were introduced in Section 3.3. The model is stochastic: it determines each nodes' movement by the random sampling of the provided cumulative distributions. We feed our mobility model generator with the following cumulative distribution functions characterizing:

- the time spent by sellers within and out of their working place;
- the time spent by customers within shops and mall;

[3] Our mobility model generator has been tested only with polygons

- and the customers' inter-arrival time

The statement lines describing these processes are embedded in the svg file and parsed by our mobility generator. In Figure 3.4 these are at the bottom but they can be placed anywhere in the document.

The statement lines 3.4 and 3.5 describe such cumulative distributions. They are composed of two parts: the right hand side, describing a cumulative distribution function, and the left hand side, describing the purpose of the formula. Their syntax is the following:

$$\underbrace{iat}_{\substack{\text{inter-arrival}\\ \text{time}}} : \underbrace{F}_{\substack{\text{cum.}\\ \text{distr.}}} \underbrace{(\alpha,\ \beta,\ ...)}_{\substack{\text{parameters of}\\ \text{the distribution}}} \tag{3.4}$$

$$stay\ [\ (sellers, [shop \mid !shop\ ]\ ) \mid (customers,\ [\ mall \mid shop\ ]\ )\ ]\ :\ \underbrace{F}_{\substack{\text{cum.}\\ \text{dist.}}} \underbrace{(\alpha,\ \beta,\ ...)}_{\substack{\text{parameters of}\\ \text{the distribution}}} \tag{3.5}$$

Our mobility generator supports five cumulative distribution functions: exponential, gamma, lognormal, weibull and linear:

- Exponential: `exp(rate=...)`
- Lognormal: `lnorm(meanlog=..., sdlog=...)`
- WeibullL: `weibull(shape=..., scale=...)`
- Gamma: `gamma(shape=..., scale=...)`
- Linear: `linear([ a<=y<=b, slope=..., intercept=...; ]) where a>=0 and b<=1`

It is also possible to consider a system of linear distributions and contiguous codomains. The line 3.4 describes the inter-arrival time of customers to the mall which, in our

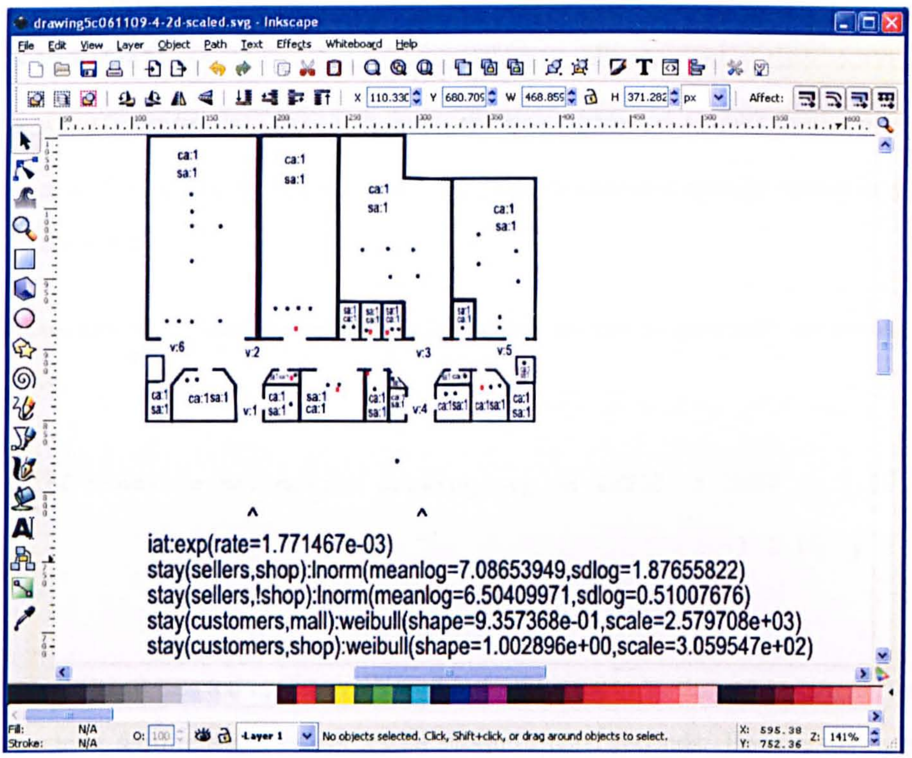

Figure 3.4: Plan and settings for the `MallMotion` configuration drawn using Inkscape (drawing.svg)

data set analysis, results in a exponential cumulative distribution (see Figure 3.4 and Section 3.5.2). The left hand side of line 3.5 tells the mobility model generator the purpose of the function alongside. As you can see on the bottom of Figure 3.4, `MallMotion` needs four statement lines following the syntax in 3.5 which mean:

- `stay(sellers, shop)`: how long sellers usually stay within their working place, i.e. a shop of the mall;
- `stay(sellers, !shop)`: how long sellers usually stay out of their working place;
- `stay(customers, mall)`: how much time customers usually spend in malls;
- `stay(customers, shop)`: how much time customers usually spend in a shop of the mall.

An example of command line, which is the one we use to generate our scenario, is as follows:

```
MM -f scenario MallMotion drawing.svg -d 43200 -i 3600 -h 1.65 \
                                              -l 1.15 -p 2     (3.6)
```

The command line 3.6 creates a shopping mall scenario lasting 12 hours, i.e. -d 43200 (a working day), cutting off an initial phase of 3600 seconds. Each node moves with a speed between 1.65 and 1.15 metres per second (values extracted from [108] [109] [110] where the walking speed of people in urban areas is analyzed) and a maximum pause time of 2 seconds before changing direction. The call graph and UML diagram of the class `MallMotion` is in the Appendix D.3.

3.5 Determining Parameters for the Shopping Mall Mobility Model

To reproduce a mobility model involving random variables such as inter-arrival times or motion times we have to specify their cumulative distribution functions. The scenario proceeds through time by generating random values satisfying these distributions.

In this section we present the process through which we determined the cumulative distribution functions needed for the mall mobility model. We initially extracted the empirical cumulative distributions from the study data describing these mobility characteristics: customers' inter-arrival time, their stay in the centre, their stay within a shop, time spent by sellers within their working place and out of it. Then we identified the standard probability distribution functions that might be used to fit the observed distributions. Finally, we inferred the best parameters to represent the closest fitting cumulative distribution functions by means of the Maximum-Likelihood Method and the Kolmogorov-Smirnov test.

Apart from modeling the shopping mall in Section 3.3, the distributions derived in this case study can be used as a starting point for modeling new scenarios. In the following section we firstly introduce the mathematical fundamentals and principles that were used during the analysis.

3.5.1 Mathematical fundamentals

For the statistical analysis we took the empirical data and calculated: interarrival time of the customers at the mall and how long sellers are in and out of their shops as well as the time spent by the customers in shops and in the mall.

The definition of interarrival time is as follows:

Definition: Let $s_1, s_2, ..., s_n (n \in \mathbb{N})$ be a sequence of starting times, $s_i < s_{i+1} (i \in \mathbb{N} \wedge 1 \leq i \leq n)$. The interarrival time is the time between s_i and s_{i+1}.

$$iat = s_{i+1} - s_i$$

Once the empirical distributions have been identified, we need to find the theoretical probability distributions (or Probability Density Function) that best fit the observations. After that, we can derive the corresponding cumulative distribution functions. A probability distribution $f(x)$ of a random variable X describes the density of probability for this random variable to occur at a given point in the sample space. Namely,

$$P(X \in B) = \int_B f(x)dx \qquad \text{and} \qquad \int_{-\infty}^{\infty} f(x)dx = 1$$

where B is any set of real numbers and $f(x)$ is a nonnegative function.

The Cumulative Distribution Functions $F(x)$ completely describe the probability that a given value X drawn from a distribution will be less than or equal to some specified value x:

$$F_X(x) = P(X \leq x) \qquad \text{for} -\infty < x < +\infty$$

where $P(X \leq x)$ means the probability associated with the event $X \leq x$. The CDF of X can be defined in terms of the probability density function $f(x)$ as follows:

$$F(x) = \int_{-\infty}^{x} f(t)dt$$

A cumulative distribution function $F(x)$ has the following properties:

1. $0 \leq F(x) \leq 1$ for all x

2. $F(x)$ is non decreasing [i.e. if $x_1 < x_2$, then $F(x_1) \leq F(x_2)$]

3. $\lim_{x \to +\infty} F(x) = 1$ (since X takes on only finite values)

At first we consider a set of theoretical distributions to be chosen based on a hypothesis. To decide the theoretical probability distributions we first observe the coefficient of variation of the empirical data, which is larger than one. Only distributions that meet this requirement are considered. The coefficient of variation c_v is a normalized measure of dispersion of a probability distribution, defined as the ratio of the standard deviation σ of a distribution to its arithmetic mean μ (see Table 3.6):

$$c_v = \frac{\sigma}{\mu}$$

Based on c_v we have selected the following density functions to test:

- Exponential Distribution

$$f(t) = \frac{1}{\beta}e^{-\frac{t}{\beta}}, t \geq 0$$

- Gamma Distribution

$$\Gamma(\alpha) = \int_0^{\infty} e^{-x}x^{\alpha-1}dx, \alpha > 0$$

$$f(t) = \frac{\lambda^{\alpha}t^{\alpha-1}e^{-\lambda t}}{\Gamma(\alpha)}, t \geq 0$$

- Lognormal Distribution

$$f(t) = \frac{1}{t\sigma\sqrt{2\pi}}e^{(-\frac{(\lg(t)-\mu)^2}{2\sigma^2})}, t > 0$$

- Weibull Distribution

$$f(t) = \frac{\alpha}{\beta}(\frac{t}{\beta})^{\alpha-1}e^{-(\frac{t}{\beta})^{\alpha}}, t \geq 0$$

To infer the optimal parameters for the empirical distribution we used the Maximum-Likelihood Method [111] for each of the above distributions. After that, the quality of fitting to the empirical data set has to be evaluated. The best-known goodness-of-fit test is the Chi-square test for goodness of fit [112]. The K-S test furnishes us with an alternative to the Chi-square test for goodness of fit [113]. The K-S test may be preferred over the Chi-square test for goodness of fit when the sample size is small [114]. Our data is continuous and the amount of measured data is quite small. Thus, we decided to use the K-S test.

The Kolmogorov-Smirnov's statistic defines the distance D between the theoretical distribution $F(x)$ and the empirical distribution $E(x)$ evaluated at x as

$$D = Max_x |F(x) - E(x)|$$

$F(x_i)$ and $E(x_i)$, evaluated at x_i, are defined as

$$F(x_i) = P(X \leq x_i)$$

and

$$E(x_i) = \frac{\#X \leq x_i}{n} = \frac{i}{n} \qquad i = 1, 2, ..., n$$

The lower the value D is, the better the theoretical distribution fits to the empirical distribution. The analysis that follows has been performed with the statistical computing tool R [67]. By loading the MASS (Modern Applied Statistics with S) package we could apply the Maximum-Likelihood Method via the *fitdistr* command and K-S test by means of *ks.test*. K-S test helps us to select the most fitting theoretical distribution.

3.5.2 Data Set Analysis

Our shopping mall mobility model distinguishes between sellers and customers dynamics. In this section we respectively describe sellers and customers dynamics and present the results of the analysis of customers' interarrival time and their staying in shops and in the mall as well as the analysis of the time spent by sellers in and out of their working place. As mentioned in Section 3.1 we were able to accomplish that by exploiting fixed nodes (motionless smart phones left by the tills) in the shopping centre where we run our experiment.

Customers' Distributions

To model customer's dynamics the mobility model generator needs to know the cumulative distributions describing their interarrival time and how much time they spend in shops and in the mall. After skimming our data set and identifying devices carried by customers (as described in Section 2.5), we conducted statistical analysis on our data to extract such distributions. By exploiting fixed nodes in seven shops during our experiment we were able to see how long customers use to spend in a shop. We also extracted the customers' interarrival time distribution at the mall by considering fixed nodes in the shops located by the entrance of the centre. Such nodes were no more than one metre from the entrances. The interarrival time distribution shows how frequently customers arrive at the mall. The cumulative distributions for the four chosen distributions along with the determined parameters are plotted against the empirical cumulative interarrival time distribution in Figure 3.5. The figure shows the fitting of the four different theoretical distributions.

The table 3.1 displays the results determined by the Maximum-Likelihood Method on the four chosen distributions to approximate the customers' interarrival time and their distances generated by the K-S test. The analysis shows that the exponential distribution is the best approximation for the interarrival time of customers at the shopping centre, although the weibull distribution shows a very small difference. Based on these results, we use the exponential cumulative distribution function defined by its *rate* parameter β for the interarrival time of customers at the mall.

Distribution	Parameters	K-S test distance
exponential	$\beta = 1.771467e-03$	$D = 0.1144$
gamma	$\alpha = 5.949694e-01$ $\lambda = 2.000000e-03$	$D = 0.2304$
lognormal	$\mu = 4.6555679$ $\sigma = 3.7874265$	$D = 0.2944$
weibull	$\alpha = 0.54584038$ $\beta = 641.05022912$	$D = 0.1409$

Table 3.1: Results of Maximum-Likelihood Method and K-S test for customers' interarrival time at the mall.

Additionally, we perform analysis on the time spent by customers respectively in the mall and in shops. We could collect such information because we left static nodes (our smart phones) in some shops, which could detect the presence of devices on the entire

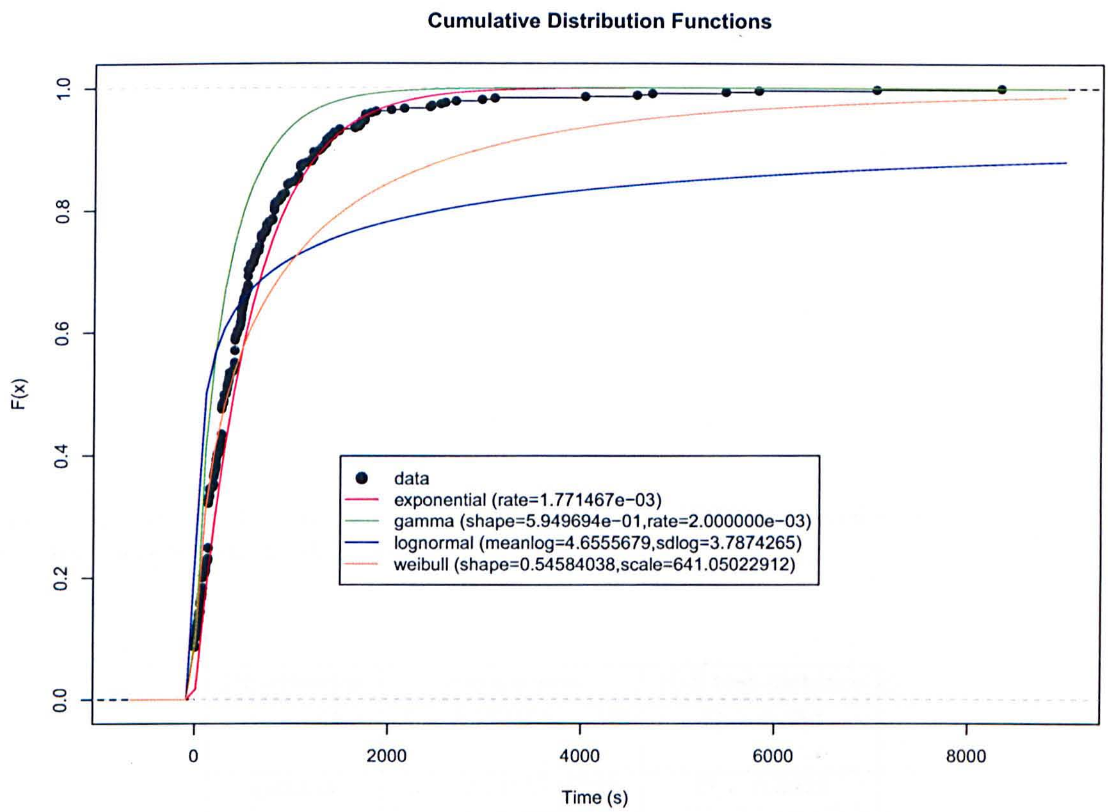

Figure 3.5: Cumulative Distribution Functions of customers' interarrival time at the shopping centre

surface of the shops we are taking into account. The parameters extracted by Maximum-Likelihood Method and the fitting markers for the four theoretical distributions are shown in tables 3.2 and 3.3. The weibull distribution defined by its *shape* α and *scale* β expresses the best fit to the empirical distributions in both cases, even though there is only a small difference with the K-S distance of the exponential and weibull distributions. Once they have been identified, we can derive the cumulative distributions described by their respective parameters. Figures 3.6 and 3.7 confirm the K-S test results.

Distribution	Parameters	K-S test distance
exponential	$\beta = 3.756779e-04$	$D = 0.0647$
gamma	$\alpha = 14.944169188$ $\lambda = 0.01$	$D = 0.3708$
lognormal	$\mu = 7.27566056$ $\sigma = 1.21560108$	$D = 0.1083$
weibull	$\alpha = 9.357368e-01$ $\beta = 2.579708e+03$	$D = 0.0639$

Table 3.2: Results of Maximum-Likelihood Method and K-S test to analyse the time spent by customers within the shopping mall.

Distribution	Parameters	K-S test distance
exponential	$\beta = 3.274162e-03$	$D = 0.353$
gamma	$\alpha = 2.5463731229$ $\lambda = 0.0100000000$	$D = 0.3922$
lognormal	$\mu = 5.330815897$ $\sigma = 0.690820187$	$D = 0.3663$
weibull	$\alpha = 1.002896e+00$ $\beta = 3.059547e+02$	$D = 0.3519$

Table 3.3: Results of Maximum-Likelihood Method and K-S test to analyse the time spent by customers within a single shop.

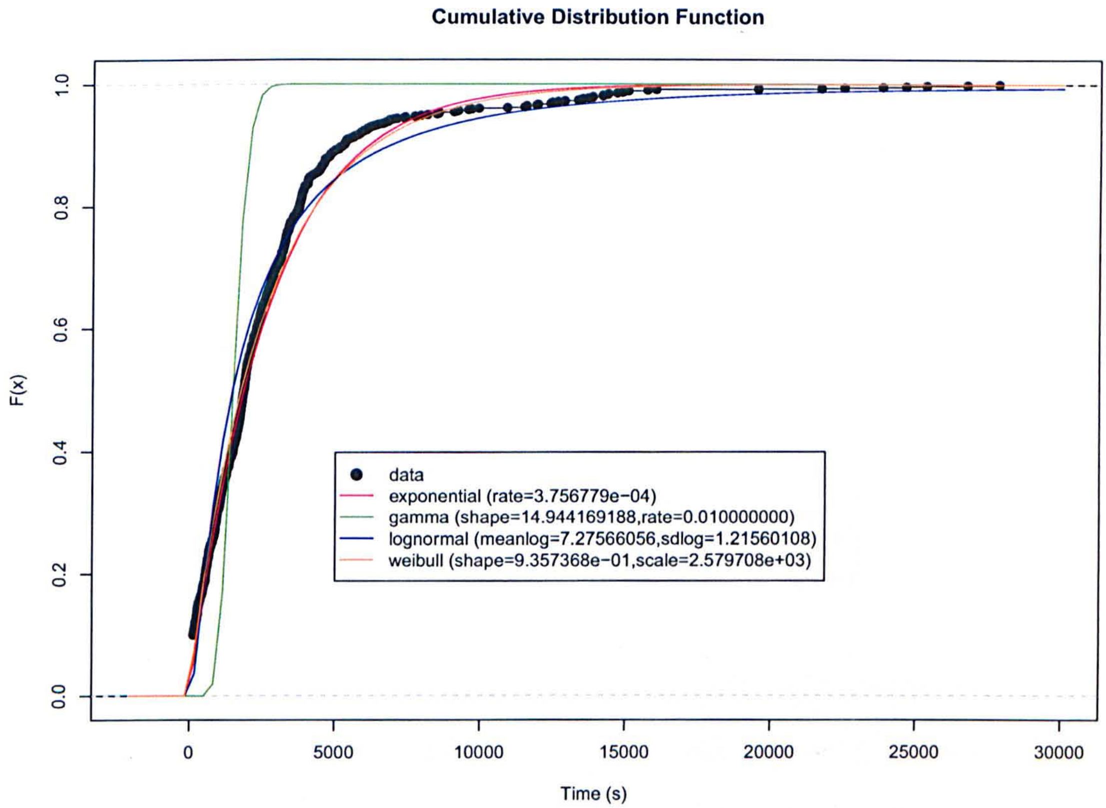

Figure 3.6: Cumulative Distribution Functions of the time spent by a customer in the shopping centre

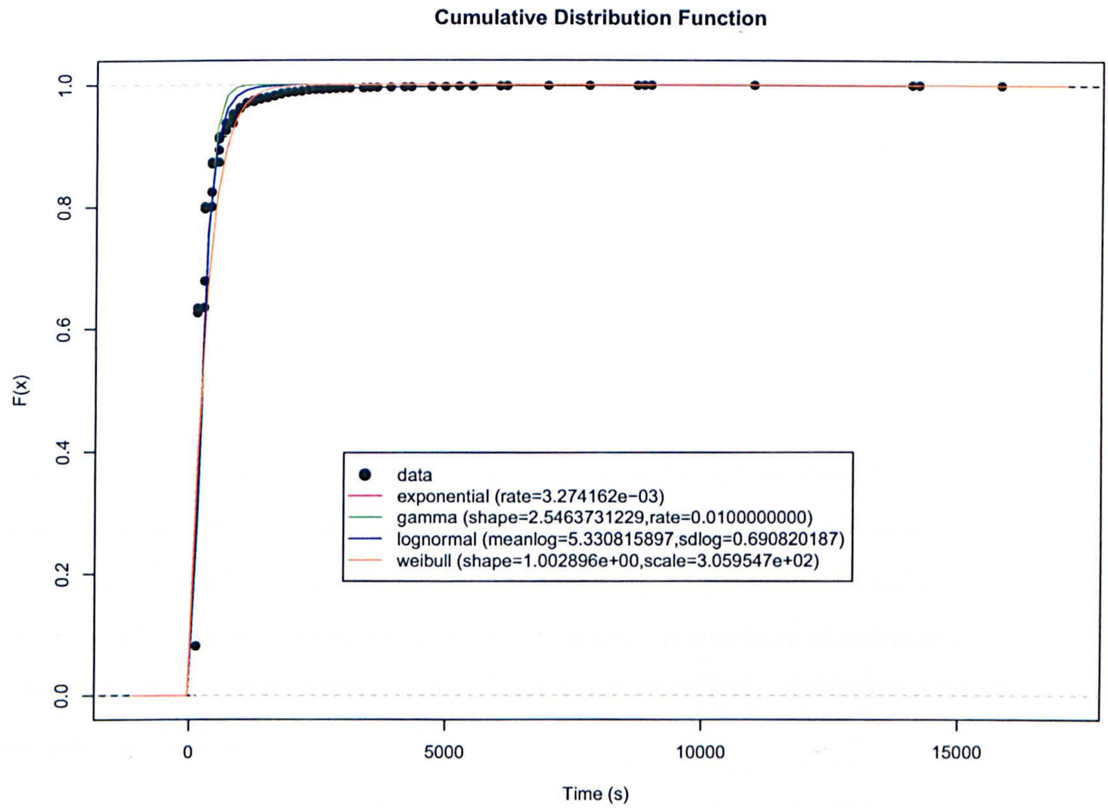

Figure 3.7: Cumulative Distribution Functions of the time spent by a customer within a shop

Sellers' Distributions

In the same way, to model sellers' dynamics, the mobility model generator needs to know the cumulative distributions describing their motions. Therefore, we conducted a similar statistical analysis to determine how long sellers were in and out of their workplace.

By exploiting fixed nodes (motionless smart phones left by the tills) in our experiment we were able to see when clerks and shop assistants (carrying our smart phones) were in their working place or somewhere else, e.g. lunchbreak, work, personal needs, etc. We assume sellers are out of their workplace if their phone does not reply to more than one periodic scan, i.e. more than 268 seconds interval time. In all of the shops except one, the Bluetooth connectivity range of our smart phones could cover the entire area of the shop.

The candidate cumulative probability distributions with the determined parameters are plotted against the empirical data distribution in Figures 3.8 and 3.9. The Tables 3.4 and 3.5 list the function parameters determined by the Maximum-Likelihood Method and the distances generated by the K-S test for sellers located within and out of their workplace. The analysis shows that the lognormal distribution is the best fit, even though the weibull and gamma distributions show a very small difference. Based on these results, we use the lognormal cumulative distribution functions defined by its parameters μ and σ for the time spent by sellers within and out of their working place. A summary of parameters (min and max value, 1st and 3rd quartiles, median and mean) describing our empirical distributions are given in Table 3.6

3.6 Summary

There are essentially two possible types of mobility patterns that can be used to evaluate delay tolerant and mobile ad hoc network protocols and applications: real and synthetic traces. Real traces are a useful method of empirical investigation, but they are usually unavailable in large numbers for many reasons: retrieving these information is extremely difficult and expensive, since this process implies that the movements of a representative

Distribution	Parameters	K-S test distance
exponential	$\beta = 1.731800e - 04$	$D = 0.4242$
gamma	$\alpha = 2.874416e + 00$ $\lambda = 2.000000e - 03$	$D = 0.3651$
lognormal	$\mu = 7.08653949$ $\sigma = 1.87655822$	$D = 0.1405$
weibull	$\alpha = 0.5371302$ $\beta = 2930.4229547$	$D = 0.173$

Table 3.4: Results of Maximum-Likelihood Method and K-S test to analyse time spent by sellers in their workplace.

Distribution	Parameters	K-S test distance
exponential	$\beta = 0.0012933264$	$D = 0.4047$
gamma	$\alpha = 2.575417584$ $\lambda = 0.003138834$	$D = 0.2097$
lognormal	$\mu = 6.50409971$ $\sigma = 0.51007676$	$D = 0.1902$
weibull	$\alpha = 1.7302969$ $\beta = 854.3538448$	$D = 0.2367$

Table 3.5: Results of Maximum-Likelihood Method and K-S test to analyse time spent by sellers out of their workplace.

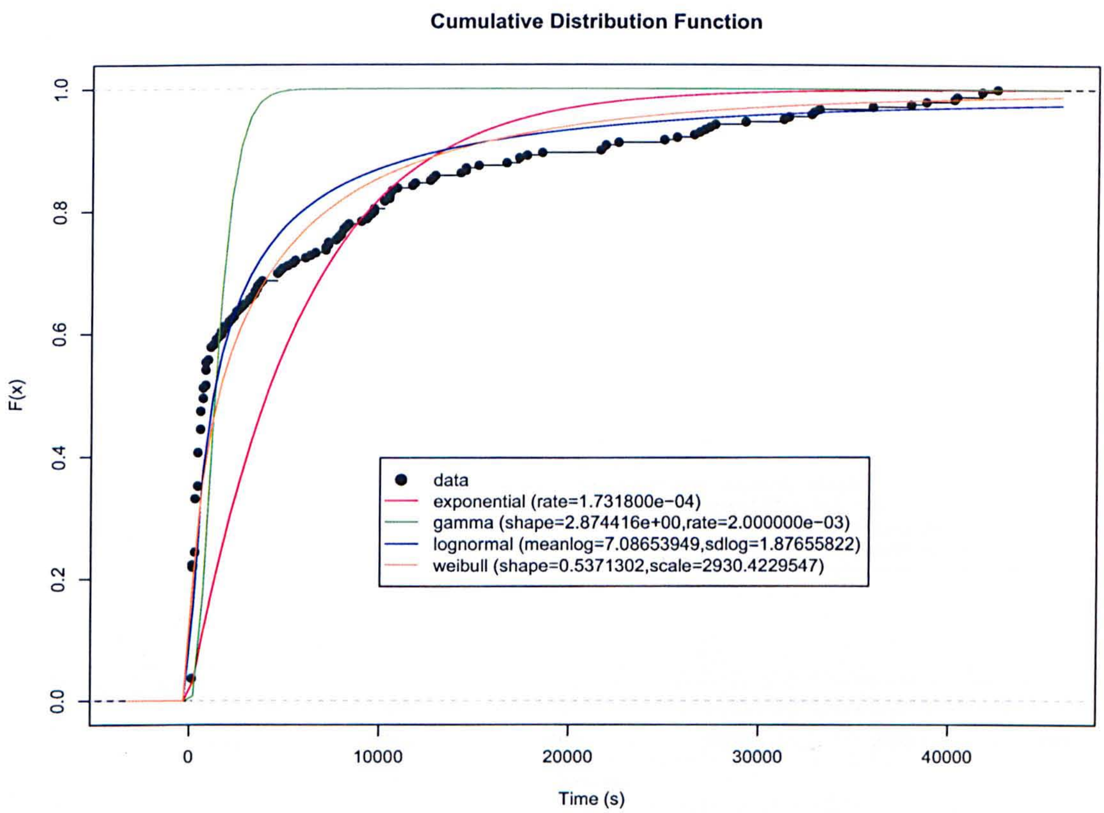

Figure 3.8: Cumulative Distribution Functions of time spent by sellers in their workplace

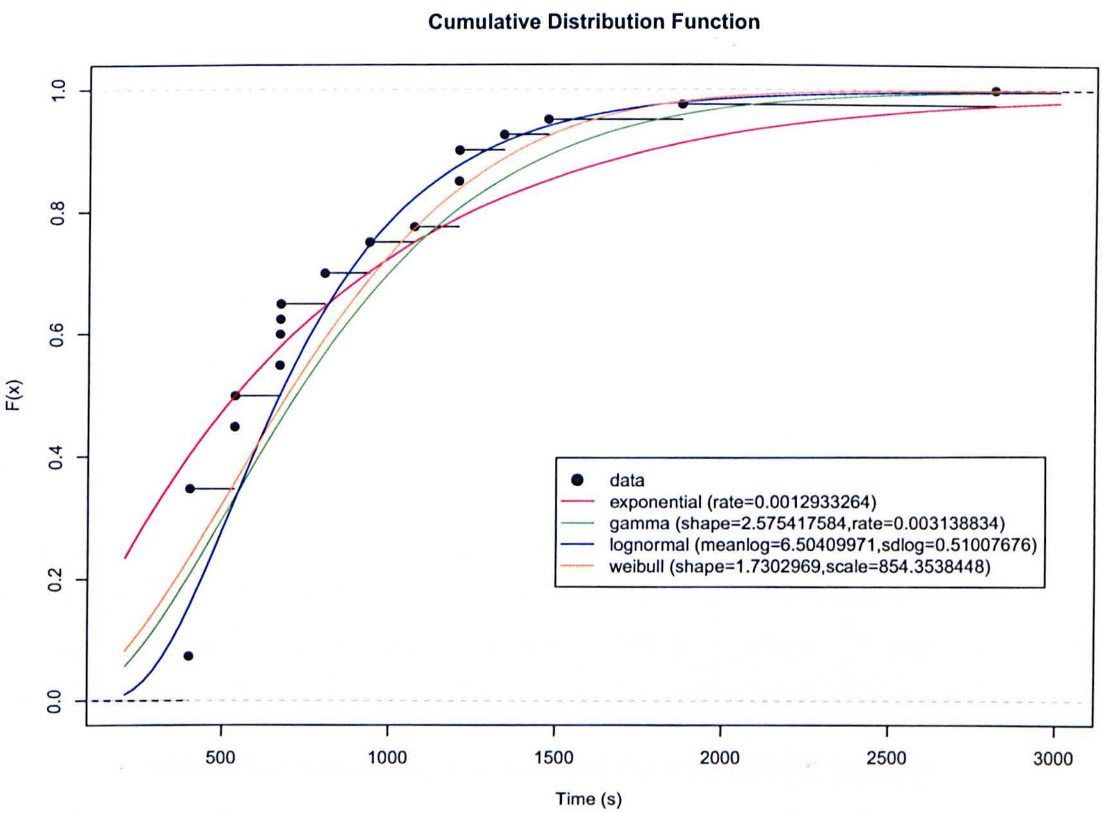

Figure 3.9: Cumulative Distribution Functions of the time spent by sellers out of their workplace

	Min.	1st Quartile	Median	Mean (μ)	3rd Quartile	Max.	St. Dev. (σ)
Customers' Interarrival Time	0.001	133.500	313.000	564.5037	669.000	8318.000	873.2157
Customers in the mall	134	739	1841	2662	3273	27800	3349.755
Customers in shops	133	134	134	305.4	268	15800	618.452
Sellers located in working place	133	268	670	5774	7330	42440	9878.209
Sellers out of working place	401	402	602.5	773.2	970.5	2812	495.7557

Table 3.6: Summaries of the results of the model fitting functions.

number of users are traced in large areas (indoor and outdoor). Moreover, the collection of mobility data is not possible in certain deployment scenarios such as dangerous environments.

In the recent years, many mobility models have been proposed and many researchers have tried to refine existing models in order to make them more realistic. In this chapter we have presented a new mobility model for shopping mall environments that is based on empirical observations of the real traces and periodic mobility patterns. It is a structured mobility model, heterogeneous in both time and space, which captures several different mobility characteristics at a lower level of abstraction than many other previous models. This approach has been used to design previous mobility models [42, 44, 43].

We derived several cumulative distributions from real traces that approximate key aspects of observed behaviour in the shopping mall scenario and which form parameters of our mobility model. Such distributions might also be employed to model different kind of shopping mall-like environments. Measurements in public places and their statistical analysis help in characterizing realistic mobility models. However, different scenarios may show different characteristics. Consequently, the mobility model generator's parameters may be different for different settings. But we suggest that our observations provide a reasonable starting point for related scenarios.

Furthermore, we introduced our mobility model generation tool which generates mobility traces for the Omnet++ simulator.

In the next chapter we present simulation results using our mobility model, with the aim of reproducing the same scenario as in the real shopping mall, and compare the real and synthetic traces.

Chapter 4

Validation of the Shopping Mall Mobility Model

Measure what is measurable,

and make measurable what is not so.

Galileo Galilei

In this chapter we validate the shopping mall mobility model presented in Chapter 3 by comparing simulation results using our mobility model with real traces and the Random Way-Point model. Namely, the validation is based on the evaluation of the degree of correspondence between stochastic and empirical distributions derived from mobility models and from our data sets. We show that our mobility model is consistent with the collected contact traces within some bounds and that it produces realistic connection opportunities with a small error. In addition, we provide evidence that traditional random mobility models express mobility patterns which are quite different from this real world setting.

Using Omnet++ [53], a network simulator, we validate our mobility model by simulating the field study described in Chapter 2 and show that the model reproduces contact opportunities comparable to those seen in real traces, as characterized by the distributions of the contact duration and inter-contact time.

4.1 Background

Simulations of mobile networks strongly rely on mobility models because they have a major influence on the performance of mobile systems [35, 115, 77]. Therefore, results obtained with an unrealistic model may not reflect the true performance of a system, be it protocol or application, in real environments.

In the recent years, mobility models have been under active research. In the Chapter 3.2.1 we have introduced several mobility models which are based on assumptions about the node's mobility. The problem with many of these mobility models [35] is that they have not been validated against real environments. It is evident by inspection that established random mobility models do not simulate realistic human movements in any kind of environment. In fact, they show properties (such as the duration of the contacts between the mobile nodes and the inter-contacts time) that are quite different to those extracted from real scenarios [72, 116, 117, 118]. This analysis is confirmed by an earlier examination of the available real traces [37]. Inter-contact and contact times are typical metrics for characterising mobility in DTNs. Usually, inter-contact and contact time distributions are used in comparisons [31, 42, 41, 46, 45, 85, 119] and they are used in the same way in this chapter.

No synthetic mobility model is totally accurate because there is no way to completely model reality. However, some of the available mobility models are for specific scenarios [74, 75, 76, 77, 78, 79] which make their validity difficult for different environments. Besides, many of the available models [38, 84, 41, 44, 45, 46, 42, 43] are homogeneous in both time and space and/or capture mobility at a high level of abstraction. Therefore, existing mobility models cannot be employed to simulate more specific and heterogeneous environments such as shopping malls at a lower level of granularity.

Furthermore, many "people counting" companies offer customer counting technologies to a wide range of clients. These technologies can count people at a specific location when they cross a straight line (usually no longer of 10 metres). They are also not able to distinguish between individuals, to record how long they are in the immediate vicinity, and might miscalculate the number of people when particularly crowded. Therefore, also these kind of counting technologies cannot be employed to validate our mobility model.

Validating a mobility model is important to increase the confidence that simulations of future systems are meaningful. Evaluation of performance of applications and protocols in mobile ad-hoc delay tolerant networks is usually based on simulations. Validation of mobility models is based on the evaluation of the degree of correspondence between stochastic and empirical distributions derived from mobility models and from our data sets.

4.2 Simulation Tool

There are a wide variety of network simulators for the evaluation of protocols in delay-tolerant mobile ad-hoc networks, ranging from the very simple to the very complex. The best known simulators are the open source ns-2 [120], GloMoSim [121] and OMNet++ [53], and the commercial OpNet Modeler [122] and QualNet [123].

Cavin et al. [124] compare the simulation results of a straightforward algorithm using OpNet Modeler, ns-2 and GloMoSim. They showed that there is significant divergence between the simulators. They argue that these differences can be explained partly by the mismatch in modelling approach of each simulator and also by the different levels of detail provided to implement and configure the simulated scenarios. They believe that a hybrid approach in which only the lowest layers (i.e. MAC and Physical) and the mobility model are simulated and all the upper layers, namely from transport to application, are executed on dedicated hosts (e.g. cluster of machines) [125] would be a better solution than standalone simulations.

We have chosen OMNet++ [126, 127], an object-oriented modular discrete event[1] network simulator written in C++ and developed by András Varga [129]. The OMNeT++ simulation kernel is a class library, while models in OMNeT++ are independent of the simulation kernel. Components are written and interact with the OMNet++ simulation kernel by means of an API. The main reasons for choosing OMNet++ are that it has a generic and flexible architecture; it provides several frameworks and plug-ins for different uses, an Eclipse-based IDE, a graphical runtime environment, and a great number of other tools; it is free for academic and non-profit use, and it is a widely used platform in the global scientific community.

To run our simulations we adopted Mixim [130, 131], a simulation framework for wireless and mobile networks which uses the Omnet++ simulation engine. Figure 4.1 shows the Omnet++ Eclipse-based IDE and the graphical runtime environment. Mixim supports mobile and wireless simulations and offers detailed models of radio wave propagation, interference estimation, radio transceiver power consumption and wireless MAC protocols.

OMNeT++ can carry out large-scale simulations, only limited by the virtual memory capacity of the computer used. Because of the amount of data we processed and the number of simulations we performed, we made extensive use of the HPC (High Performance Computing) of the University of Nottingham [132]. The HPC is a cluster that comprises a mix of hardware from different procurements. The newer hardware comprises 600 compute nodes, containing either 2 quad-core processors (Intel Xeon E5472 3.0GHz) or 2 opteron processors, providing a total of 4,000 cores. All compute nodes are linked by a fast InfiniBand network, suitable for running highly parallel scientific codes. The cluster is capable of running at over 12 teraflops (12 million million calculations per second). The compute nodes have either 2GB, 16GB, or 32GB memory available. Storage of over 100TB, mostly high performance parallel storage, is shared over the entire facility.

[1] *Discrete-event simulation* concerns the modeling of a system as it evolves over time by a representation in which the state variables change instantaneously at separate points in time. These points in time are the ones at which an event occurs, where an *event* is defined as an instantaneous occurrence that may change the state of the system. Although discrete-event simulation could conceptually be done by hand calculations, the amount of data that must be stored and manipulated for most real-world systems dictates that discrete-event simulations be done on a digital computer [128].

4.3 Simulation Settings

We intend to determine whether the contact patterns observed in the real traces were reproduced by our Shopping Mall mobility model. Therefore, we tried to simulate a scenario as close as possible to the field trial experiment described in Chapter 2. The entire simulation area covers a surface of $10,880m^2$, without considering the parking area. We were very precise in drawing the shopping mall, premises and corridors as we have its original plan. The scale of the simulation playground is 2:1 (i.e. 2 pixels = 1 metre). We set the attraction level of each shop equal to 1 so that nodes have the same probability to move to any shop. These attraction level settings are acceptable for small scale environments like the shopping mall we are considering but it may not be suitable for large scale environments. We considered 25 nodes as internals (18 sellers and 7 fixed nodes); they were in the same virtual shops in which they were during the real experiment. The modelled mall can be seen in Figure 3.4. We tested the Random Way-Point model using the same number of sellers and fixed nodes, on the same floor area, with the only exception that nodes would move without taking into account the plan of the mall, i.e. walls, corridors, etc. (see Figure 3.3). The number of customers varied according to the cumulative inter-arrival time distribution. The speed of the nodes was randomly generated according to a uniform distribution between [1.65 - 1.15]m/s, based on [108] [109] [110] where the walking speed of people in urban areas is analyzed. The pause time of the nodes was drawn from a uniform distribution between [0 - 2]s. We simulated twelve hours each for six days to reproduce the experiment.

We assumed that each device was equipped with an omnidirectional antenna with a transmission range of about $30m$ in a free space propagation model, based on the measured transmission range of our smart phones in open space. We set the devices in enquiry mode as for the real experiment. Neighbor discovery was performed at approximately 120 seconds intervals plus 14 seconds for the inquiry process. We used the 802.11b MAC protocol provided by the Mixim framework and adjusted the parameters to reproduce the Bluetooth transmission range: maximum transmission power of $2.5mW$, signal attenuation threshold $-65dBm$ and carrier frequency $2.412e+9Hz$. We obtained these settings from the Bluetooth technical specifications. In our simulations we adopted an *Analogue Model* for the physical layer with a path loss coefficient alpha equal to 2.2 (see table in Appendix B.1 from [133]) and a *Decider* based on a Signal-to-Noise Ratio of 10 and centre frequency $2.412e + 9$ to classify signals as noise or potential packet. Appendices F.1 and G.1 give the full parameters settings in the configuration files *omnetpp.ini* and config.xml, while the Appendices H.1 and H.2 present the structure of the simulation model described in the NED files of the Omnet++ simulation framework. Initial simulation of communication range verified that these parameters reproduce the observed Bluetooth transmission range.

4.4 Results

As previously observed, our shopping mall mobility model distinguishes between sellers' and customers' dynamics. In this section we present a comparison of the sellers' and customers' contact patterns generated by our mobility model with those generated by the Random Way-Point mobility model and the real traces. We also compare the contact patterns from the perspective of the two nodes considered in Section 2.4.1, for the same three cases. For this comparison the real traces were filtered using the method presented in Section 2.5 to identify customers and exclude individuals behaving like sellers. For this comparison we consider as sellers only people carrying smart phones that we provided for our experiment in the mall. We analyzed movement patterns in terms of inter-contact time and contact duration.

4.4.1 Sellers' Synthetic and Real Traces

The Figures 4.2 and 4.3 respectively compare inter-contact time and contact duration cumulative distributions between sellers on a log-log scale. In both plots, the sellers' cumulative distributions generated by our mobility model approximate quite well those extracted from the real traces. In contrast, the inter-contact time cumulative distribution based on the Random Way-Point model shows a typical exponential distribution while the contact duration is biased by fixed nodes in range with each other.

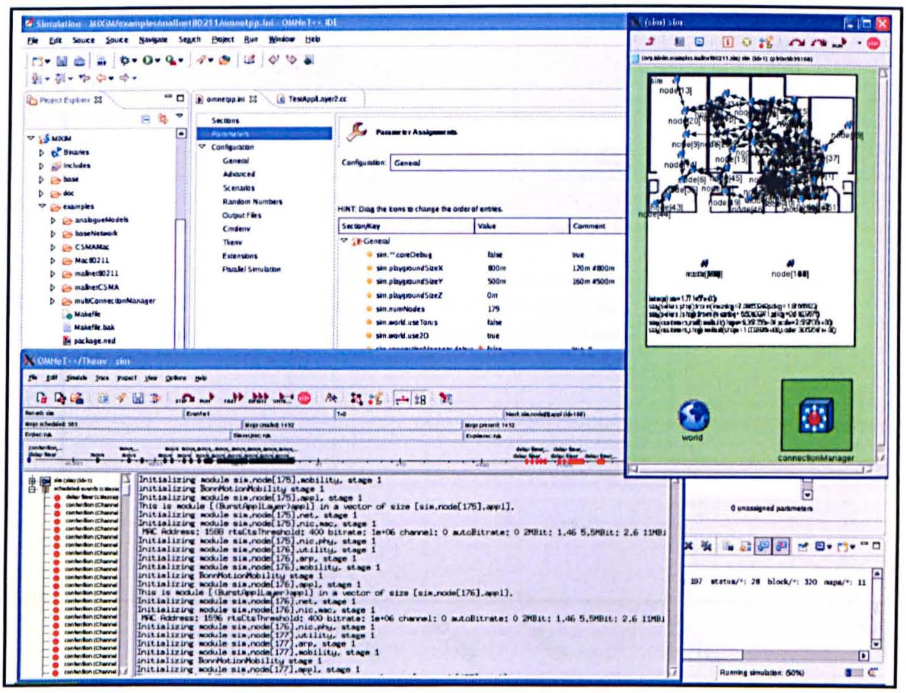

Figure 4.1: Omnet++ Eclipse-based IDE and the graphical runtime environment

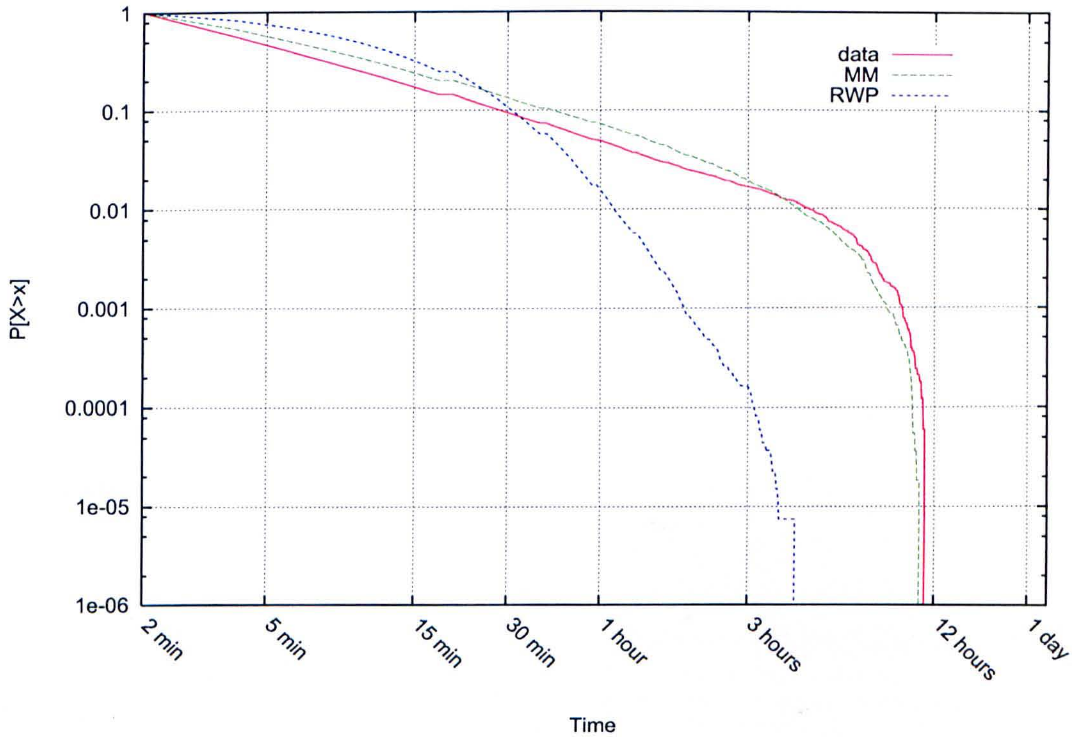

Figure 4.2: Comparison between sellers' synthetic and real traces: cumulative distributions of inter-contact time

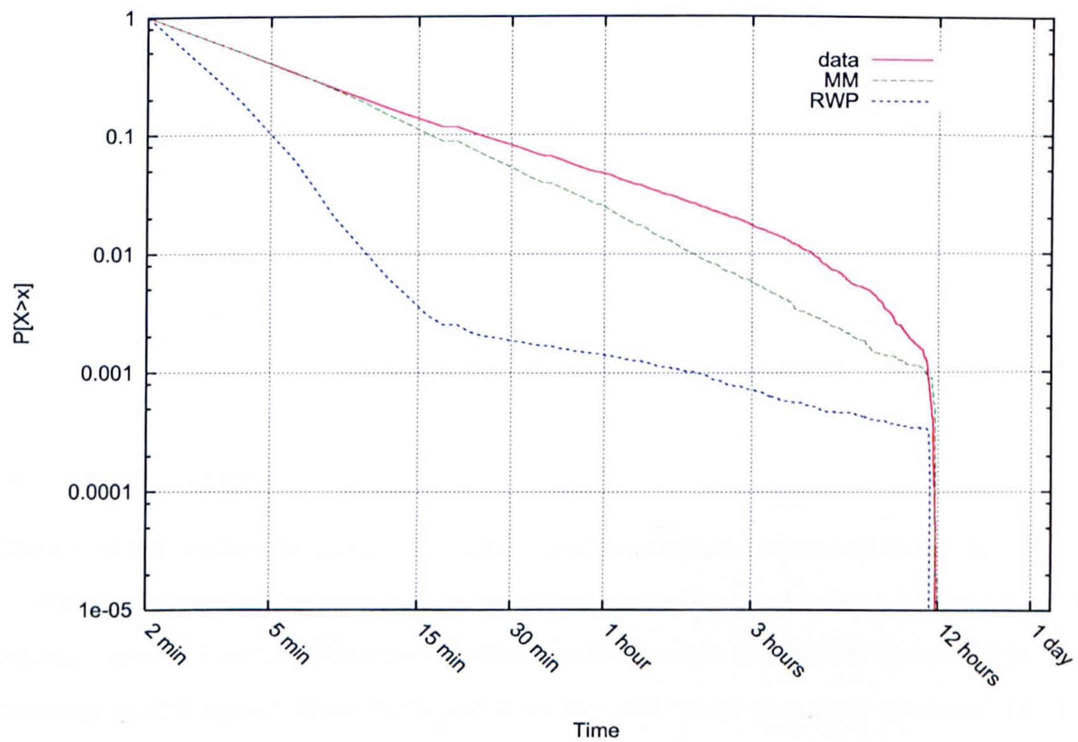

Figure 4.3: Comparison between sellers' synthetic and real traces: cumulative distributions of contact duration

4.4.2 Customers' Synthetic and Real Traces

As for sellers, Figures 4.4 and 4.5 respectively compare inter-contact time and contact duration cumulative distributions between sellers and customers on a log-log scale. Customers' inter-contact time distribution from our mobility model is a good approximation of the customers' real traces. Perhaps surprisingly, all of them express an exponential distribution. With regard to the contact time distribution, we observe that the distribution from our mobility model resembles that of the real traces, though with a power law behaviour with a more limited range than for sellers plotted in Figure 4.3. In the real mall, as observed in the left part of the plot in the Figure 2.11, customers did not spend more than about two hours at a time. Although we do not have logs from customers' devices to directly analyze inter-customers contacts, these observations from the contact traces along with those in Chapter 2 support the validaty of the sellers' and customers' mobility models which implies that customers' movement is realistic and therefore that customer contact patterns should be realistic.

4.4.3 As a Whole

Finally, in this section, we present a comparison of the contact patterns of the whole system, without distinguishing between customers and sellers. In Figures 4.6 and 4.7 we show inter-contact time and contact duration distributions between all individuals, generated by our mobility model against those extracted from the real traces and those produced by the Random Way-Point model. We observe that the inter-contact time distribution of our mobility model approximates the one from real traces. They both exhibit a heavy tailed distribution over a large range of values that can be approximated or lower bounded by the tail of a power law. We also observe a higher slope coefficient of the interpolating line compared to the the traces from Intel Research Cambridge, Cambridge Computer Lab, Dartmouth college and UCSD [1]. This shows that data related to different scenarios may be characterized by different types of power law distribution. As expected, the Random Way-Point model shows a typical exponential distribution over a smaller range of values.

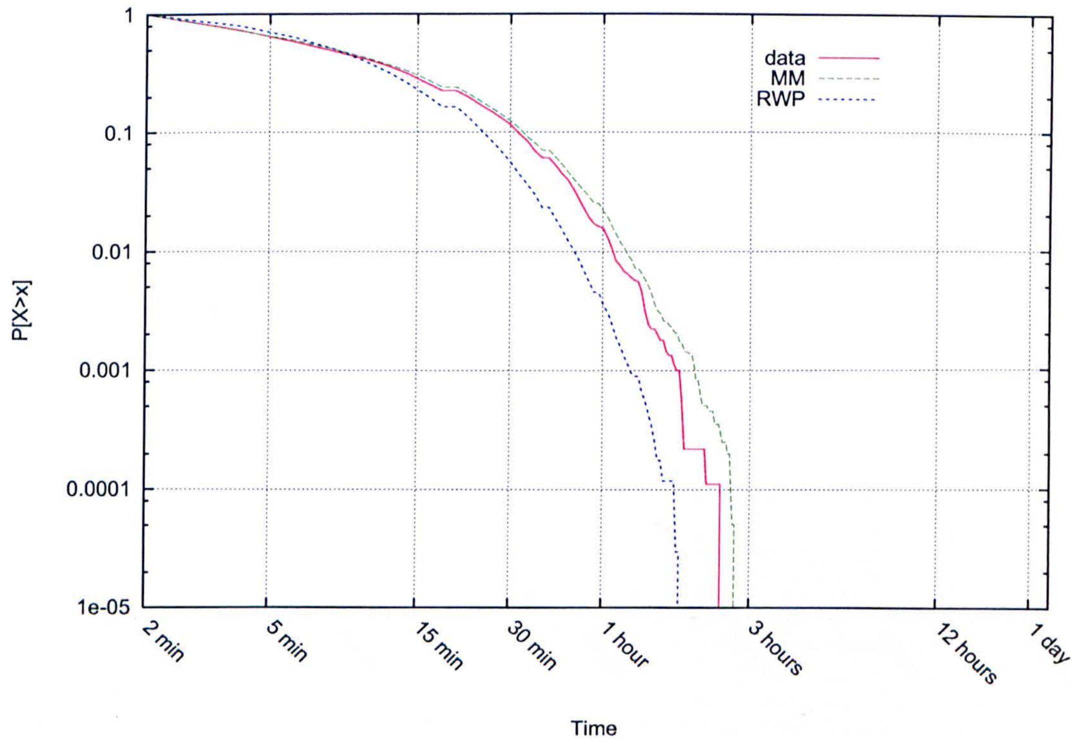

Figure 4.4: Comparison between customers' synthetic and real traces: cumulative distributions of inter-contact time

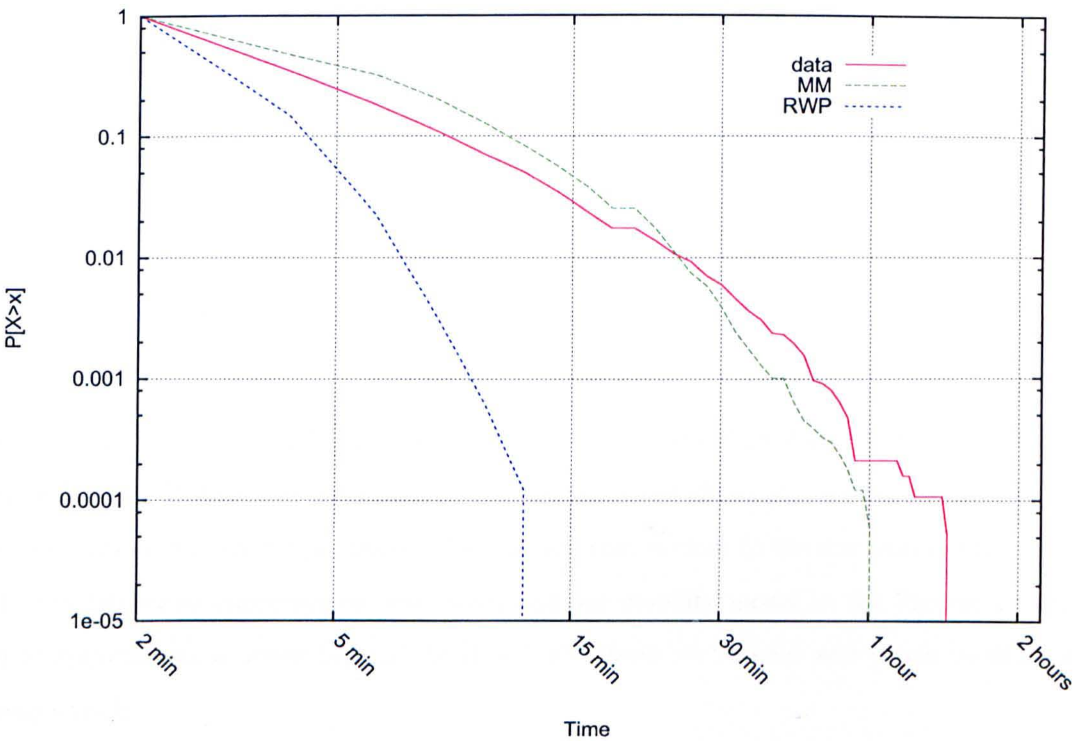

Figure 4.5: Comparison between customers' synthetic and real traces: cumulative distributions of contact duration

With respect to contact duration, our mobility model is still a good approximation of the real traces. As in Figure 4.3, the Random Way-Point model exhibits a contact time distribution which is affected by the fixed nodes which are in contact range for longer period of time.

4.4.4 Synthetic and Real Traces from a Fixed Node's Perspective

Inter-Contact Time

In this section we consider inter-contact time distributions for the fixed node considered in Section 2.4.1 (i.e. "c3a4"), which is located in the shop highlighted in red in Figure 2.1. Figure 4.8 considers neighbouring sellers Figure 4.9 considers customers while Figure 4.10 considers all the individuals together. We cannot distinguish neighbouring sellers in a Random WayPoint mobility model, as they move without boundaries within the mall, consequently, this case is omitted from Figure 4.8. It is interesting to notice that customers in Figure 4.9 show a distribution with an exponential decay. This means that such behaviour can be reproduced by traditional mobility model such as Random Way-Point and its derivatives [35]. In Figure 4.10 the Random Way-Point model shows still an exponential decay, while our mobility model produces a distribution that is close to the one seen in the traces. The distributions expressed by real traces and our mobility model in the Figures 4.8 and 4.10 approximate a power law for the time scale $[2min :\sim 2hours]$ and $[2min :\sim 6hours]$ respectively.

Contact Time

We now consider the contact time distributions for the same fixed node and its neighbouring sellers, customers and all the nodes in the shopping mall plotted in the Figures 4.11, 4.12 and 4.13 respectively. Again our shopping mall mobility model gives rise to contact time distributions which are quite close to those extracted from the real traces and much closer than the Random Way-Point mobility model.

The Random Way-Point model in Figure 4.13 produces a very few contacts duration

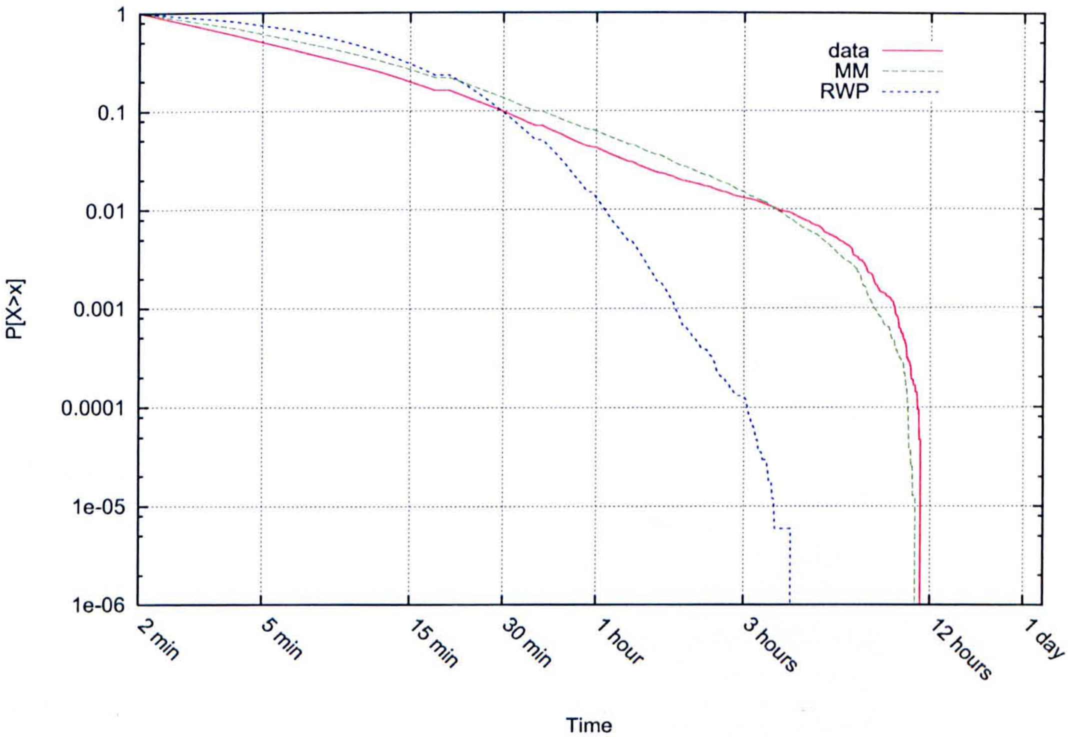

Figure 4.6: Comparison between synthetic and real traces: cumulative distributions of inter-contact time

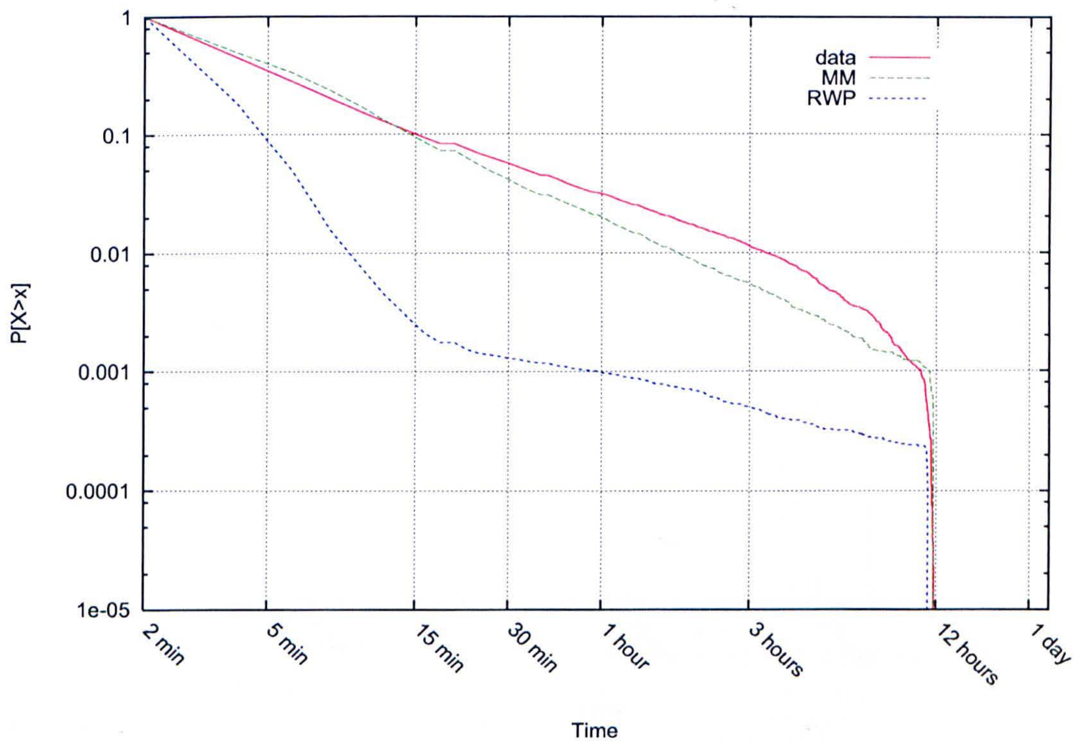

Figure 4.7: Comparison between synthetic and real traces: cumulative distributions of contact duration

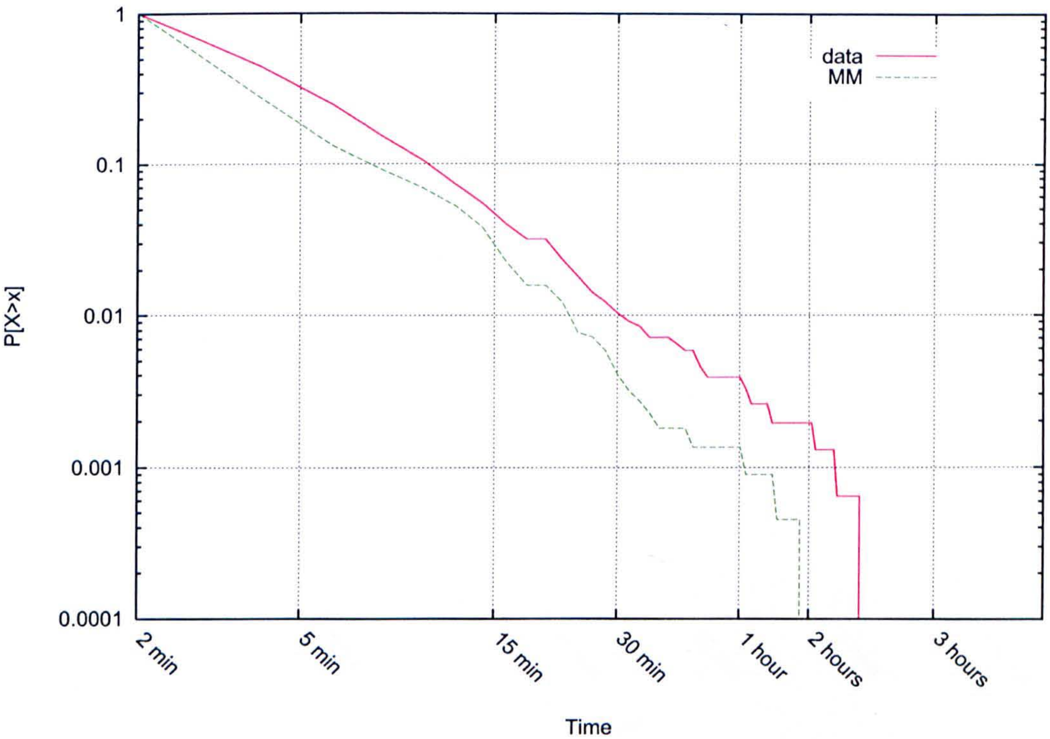

Figure 4.8: Inter-Contact Time distributions over six days between the internal fixed node "c3a4" and the neighboring sellers resulting from real traces (data) and our shopping mall mobility model (MM).

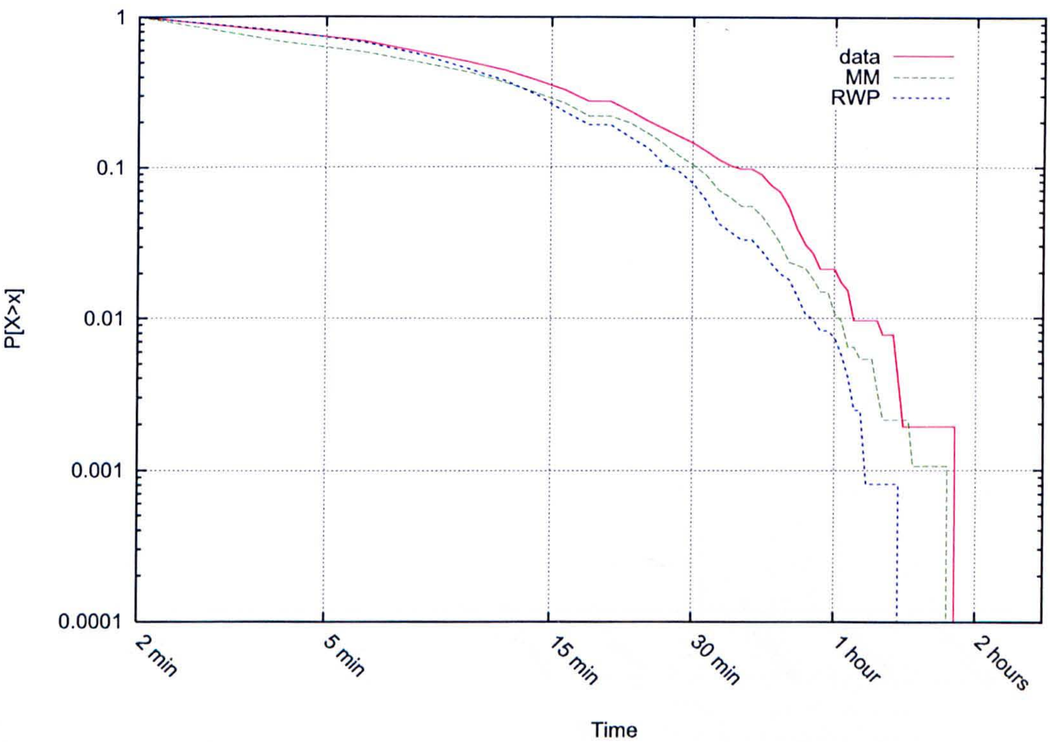

Figure 4.9: Inter-Contact Time distributions over six days between the internal fixed node "c3a4" and customers resulting from real traces (data), our shopping mall mobility model (MM), and the Random Way-Point mobility model (RWP).

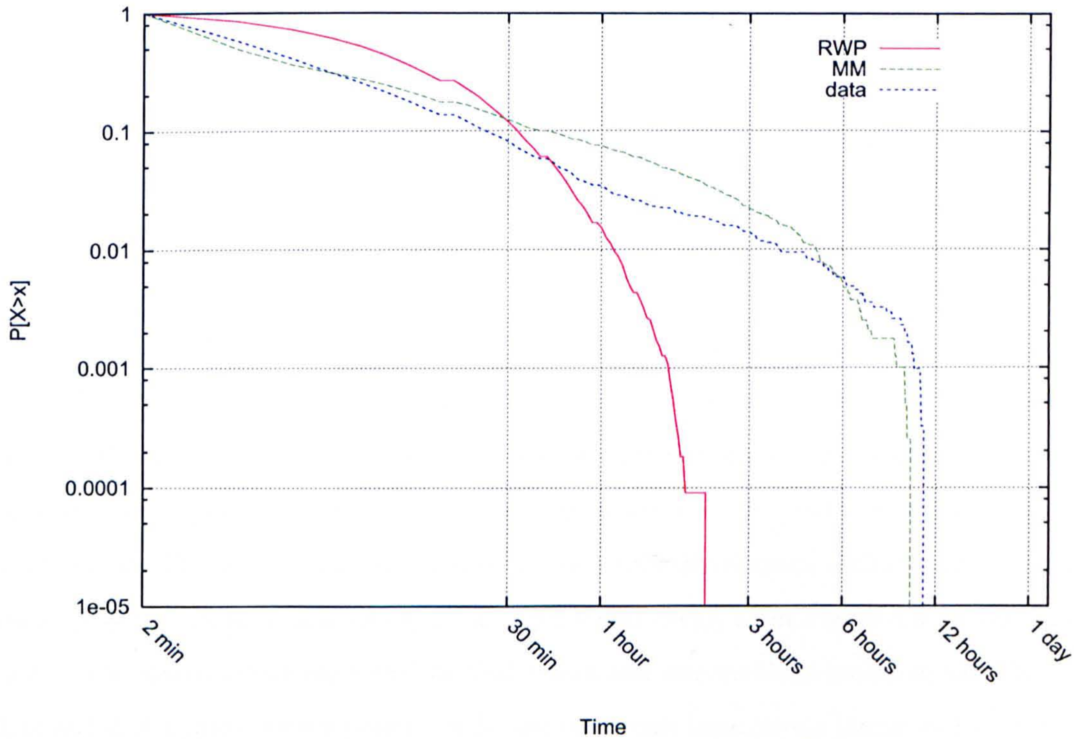

Figure 4.10: Inter-Contact Time distributions over six days between the internal fixed node "c3a4" and all the individuals resulting from real traces (data), our shopping mall mobility model (MM), and the Random Way-Point mobility model (RWP).

in the range [$\sim 7min$:$\sim 11hours$] but several contacts of about 12 hours. This is because of the 7 fixed nodes we have considered in the synthetic mobility models as well as in the real experiment conducted in the shopping mall: some of these were in range with each other most of the time. The duration of the contacts can also vary because of the values assigned to the parameters of the *Analogue Model* and the *Decider* used for the simulation (see Section 4.3), and possibly due to collisions caused by the hidden station problem [134].

4.4.5 Synthetic and Real Traces from a Mobile Node's Perspective

Inter-Contact Time

As for the previous section we plot here inter-contact times of the mobile node taken into account in Section 2.4.1 (i.e. "7398"). In the real experiment the mobile device is carried by a seller whose workplace is the same as above (see red highlighted shop in Figure 2.1).

The Figures 4.14, 4.15 and 4.16 plot the inter-contact time distributions between "7398" and neighboring sellers, customers, and all the nodes in play respectively. As for the fixed node in the section above, the inter-contact time distributions for the mobile node in our shopping mall synthetic model are close approximations of the real traces distributions. Furthermore, Figure 4.15 confirms an inter-contact time distribution with customers in the range [$2min$:$\sim 2hours$] and following an exponential decay, as in Figure 4.9 for the fixed node. The distributions expressed by real traces and our mobility model in the Figures 4.14 and 4.16 approximate a power law for the time scale respectively [$2min$:$\sim 1hour$] and [$2min$:$\sim 6hours$].

Contact Time

This final section considers the contact duration distributions of this *mobile* node with respect to neighboring sellers in Figure 4.17, customers in Figure 4.18 and all the nodes in the mall in Figure 4.19. Again our shopping mall mobility model produces a fair approximation of the contact time distributions resulting from real data. The Random Way-Point model in both Figures 4.18 and 4.19 exhibits the same distribution in the range [$2min$:$\sim 15min$],

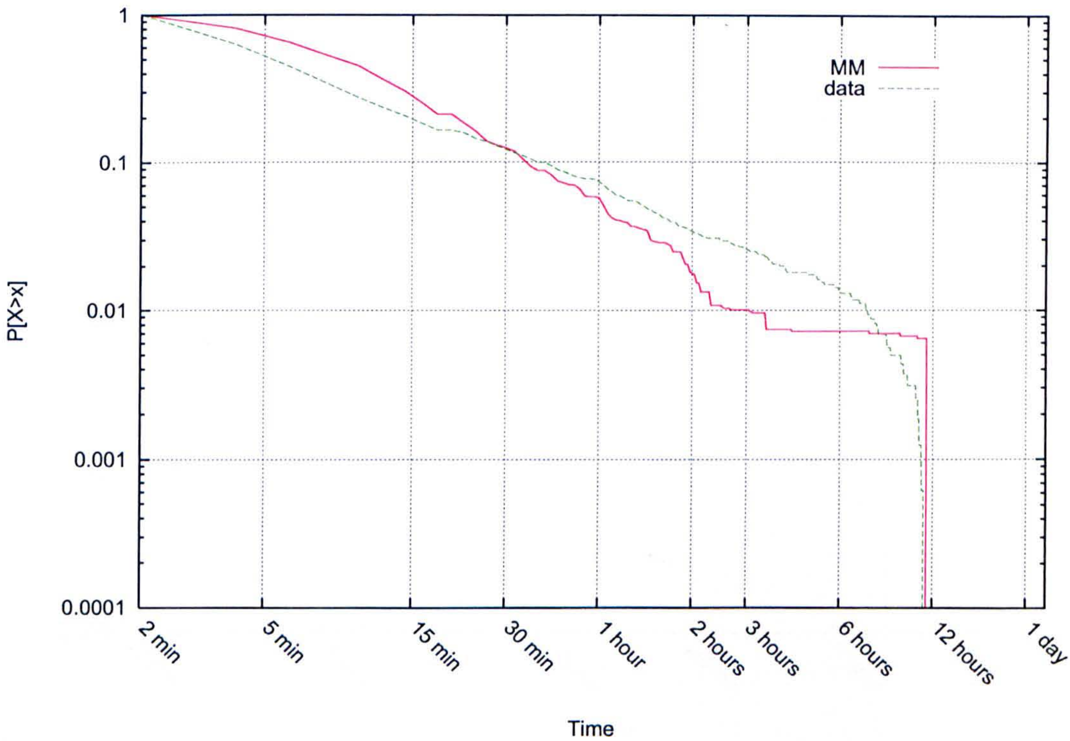

Figure 4.11: Contact Time distributions over six days between the internal fixed node "c3a4" and the neighboring sellers resulting from real traces (data) and our shopping mall mobility model (MM).

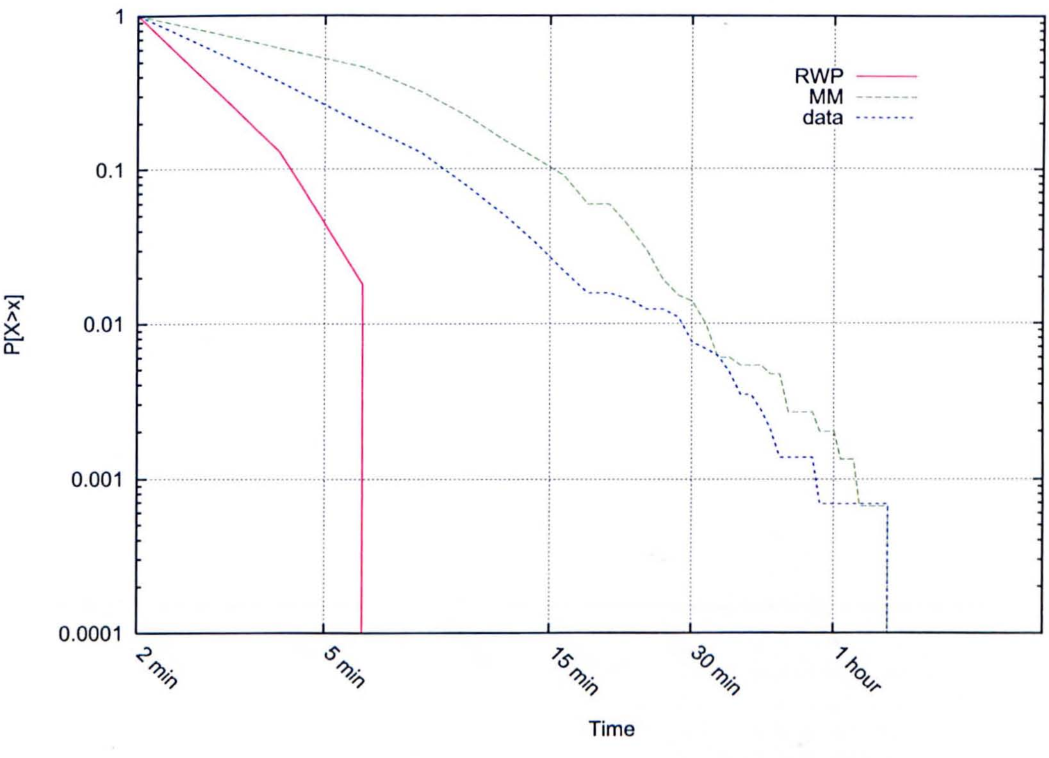

Figure 4.12: Contact Time distributions over six days between the internal fixed node "c3a4" and customers resulting from real traces (data), our shopping mall mobility model (MM), and the Random Way-Point mobility model (RWP).

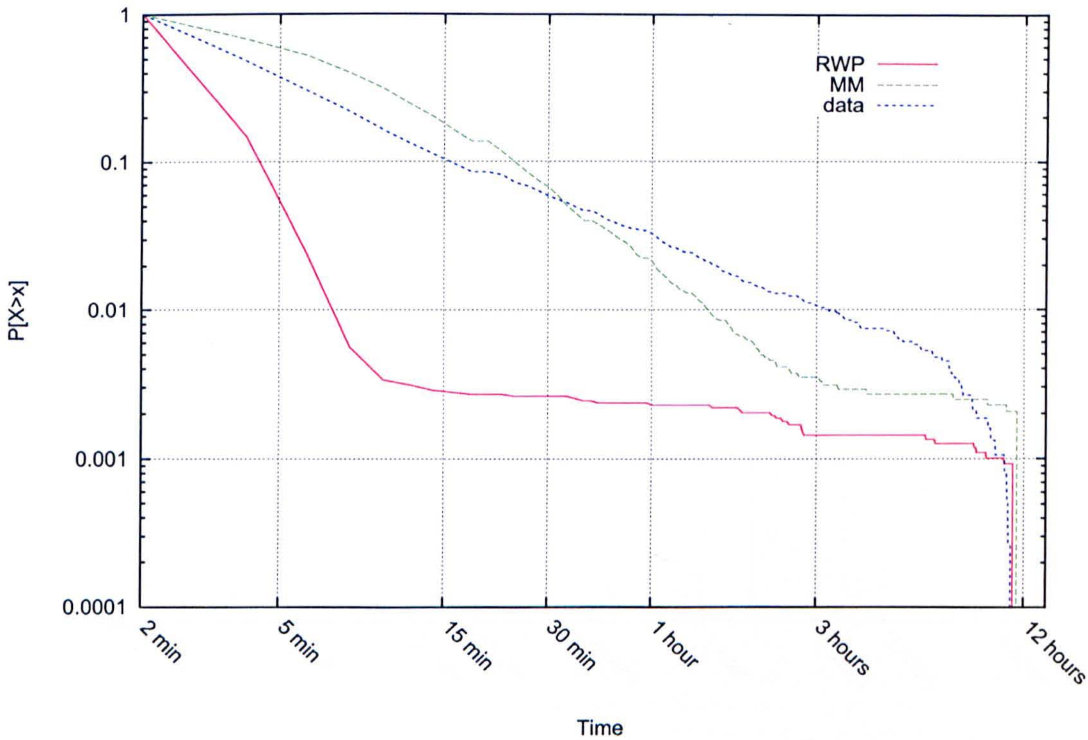

Figure 4.13: Contact Time distributions over six days between the internal fixed node "c3a4" and all the individuals resulting from real traces (data), our shopping mall mobility model (MM), and the Random Way-Point mobility model (RWP).

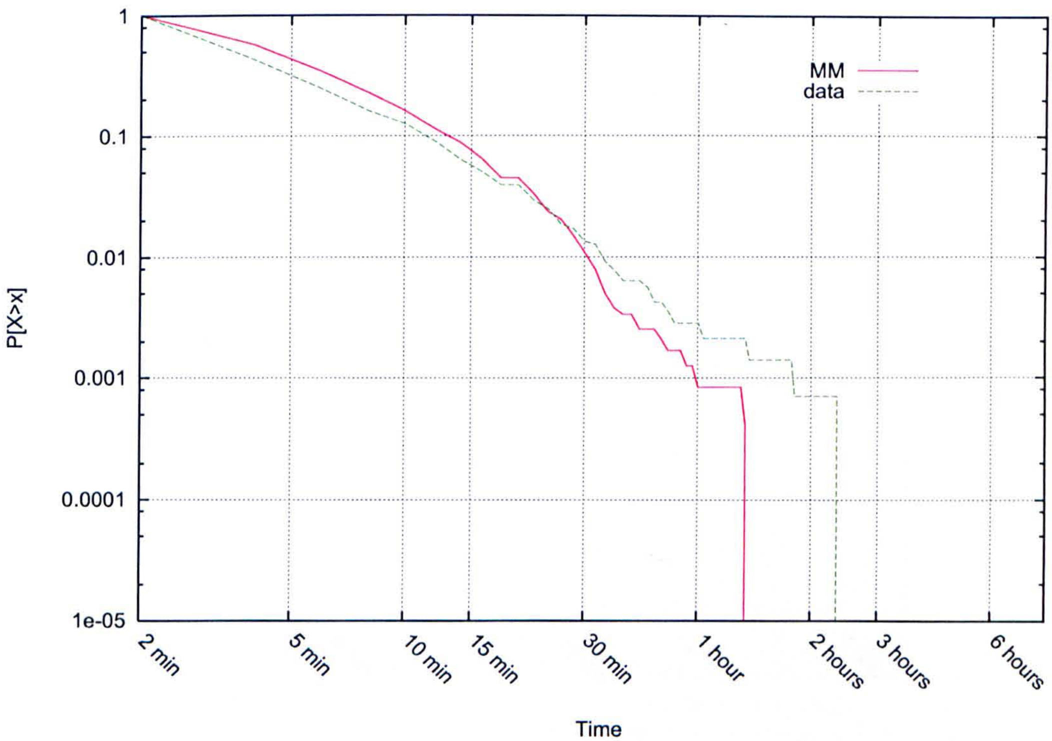

Figure 4.14: Inter-Contact Time distributions over six days between the internal mobile node "7398" and the neighboring sellers resulting from real traces (data) and our shopping mall mobility model (MM).

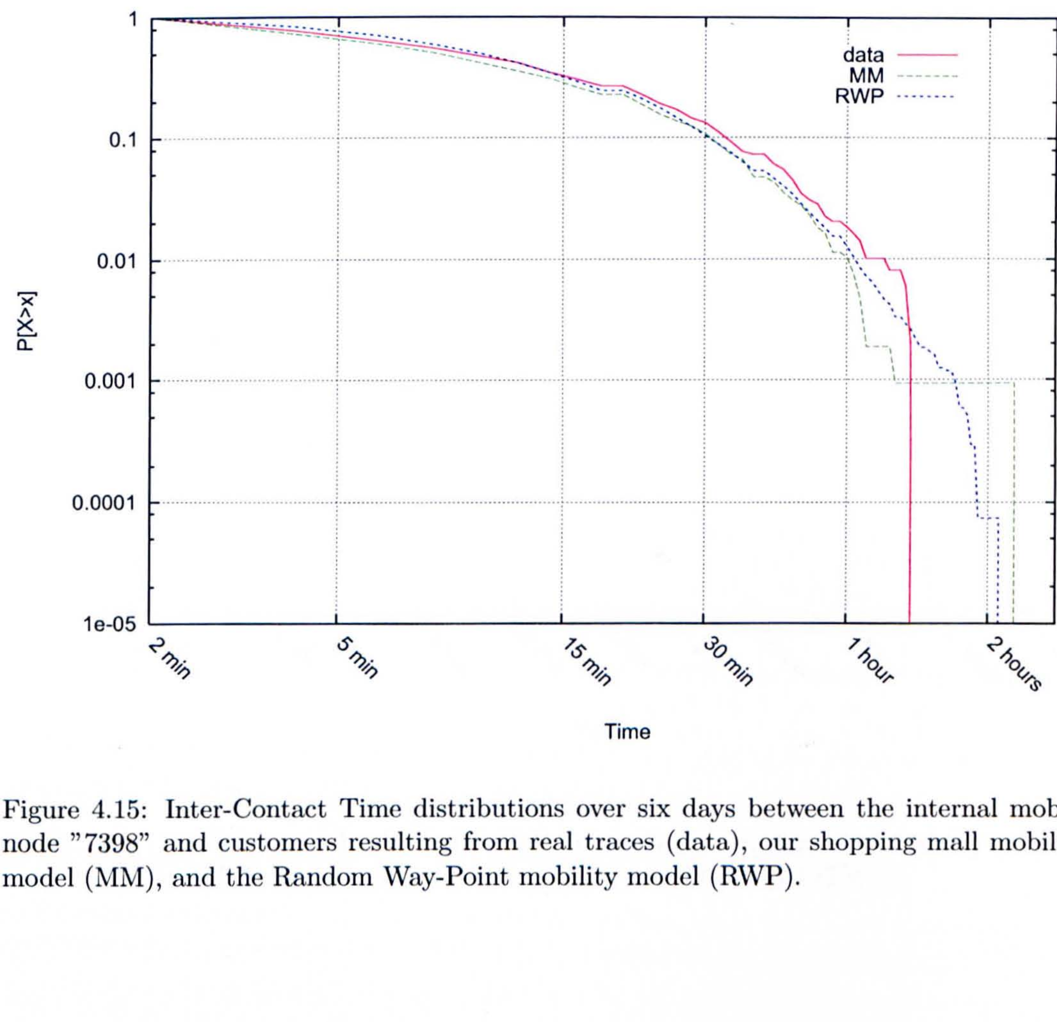

Figure 4.15: Inter-Contact Time distributions over six days between the internal mobile node "7398" and customers resulting from real traces (data), our shopping mall mobility model (MM), and the Random Way-Point mobility model (RWP).

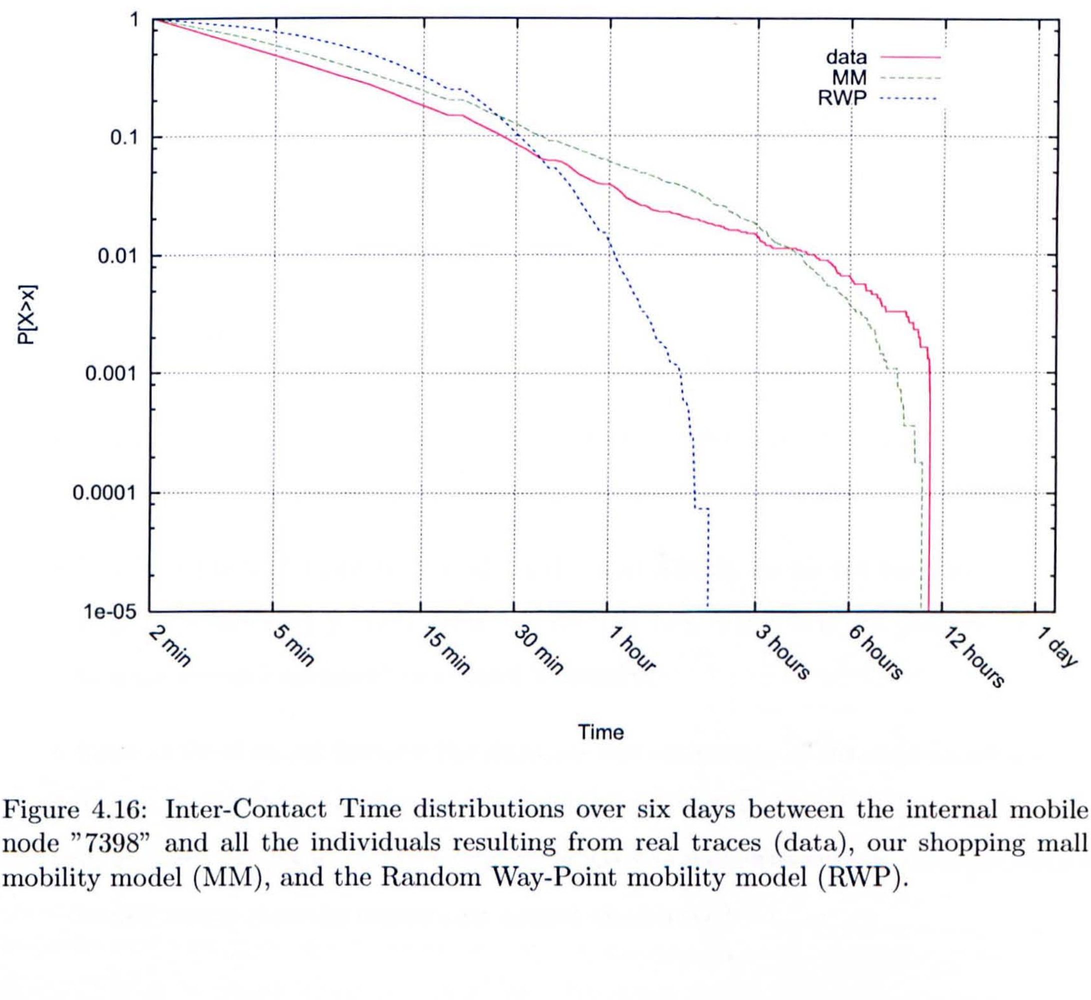

Figure 4.16: Inter-Contact Time distributions over six days between the internal mobile node "7398" and all the individuals resulting from real traces (data), our shopping mall mobility model (MM), and the Random Way-Point mobility model (RWP).

which is very different from the observed distribution.

4.5 Limitations

There are several limitations regarding the evaluation of the Shopping Mall mobility model presented in this thesis and I want to point them out here:

- The mobility model has only been evaluate considering a particular scenario in a shopping mall, i.e. where the contact traces have been collected. Thus, we do not know to what extent our model can reproduce different scenarios.
- It is also hard to see if such an evaluation applies with respect to different malls. Evaluations of this model over larger scale domains has not been conducted yet and will be an interesting topic for future study. It would be useful to collect contact traces in other malls and see the accuracy of the model.
- The model has not been validated over different time scales. The size of our data set allows us to compare synthetic traces against six days real world contact traces.
- This is a physical movement model and unfortunately we do not have contact data from the customer's point of view (see Section 2.8). Thus, it is not possible to know to what extent customers' movement is realistic.
- Some of the data set features like duration and periodicity of the experiment also influence the validation of the mobility model at different degrees of confidence. Namely, short event lengths is limited by the granularity of measurement and similarly, events lasting longer than the experiment cannot be observed.

4.6 Summary

In this chapter we have sought to validate our shopping mall mobility model by comparing it with real traces and the Random Way-Point model. We simulated the same experiment and

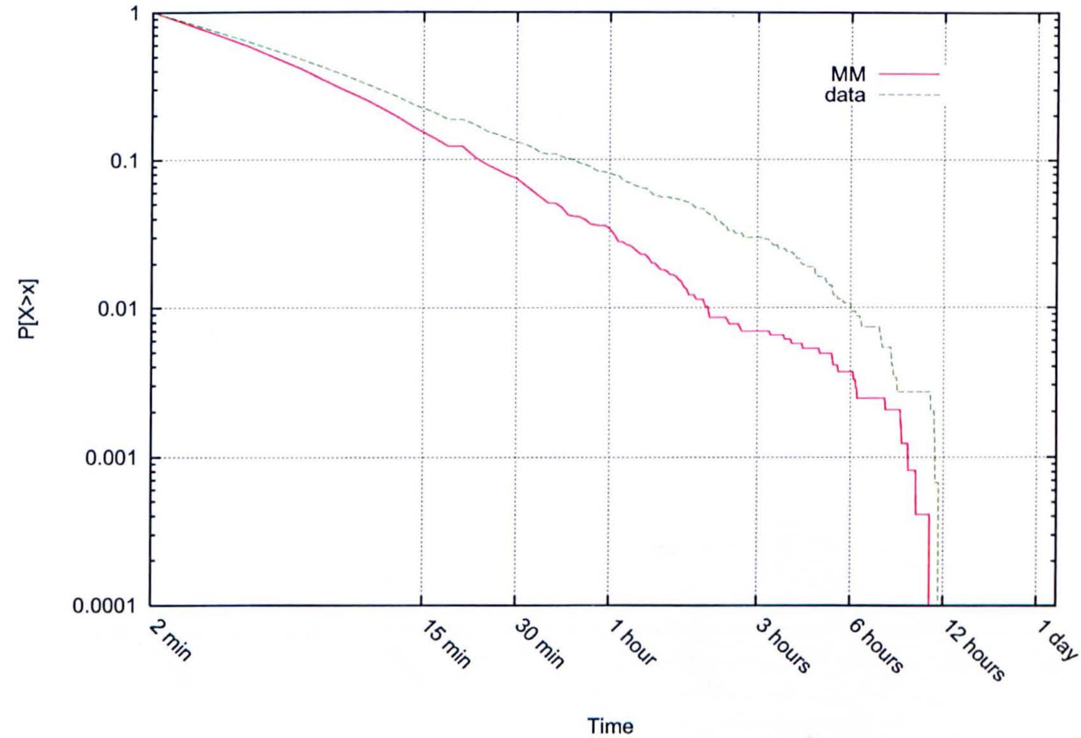

Figure 4.17: Contact Time distributions over six days between the internal fixed node "7398" and the neighboring sellers resulting from real traces (data) and our shopping mall mobility model (MM).

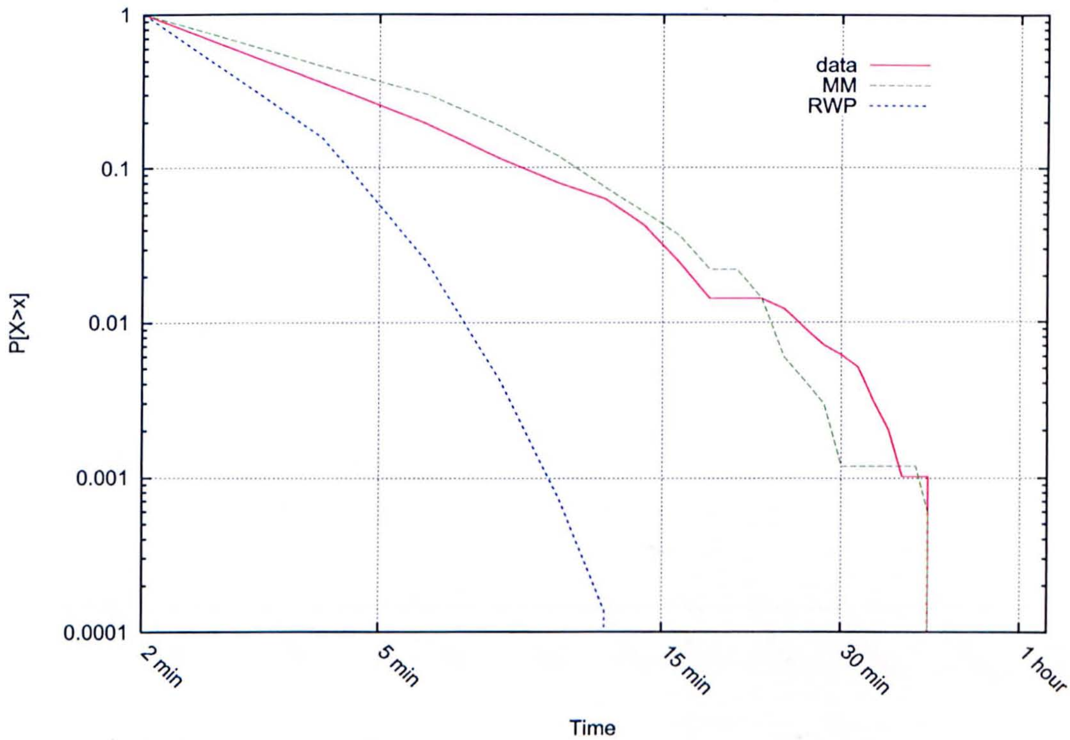

Figure 4.18: Contact Time distributions over six days between the internal fixed node "7398" and customers resulting from real traces (data), our shopping mall mobility model (MM), and the Random Way-Point mobility model (RWP).

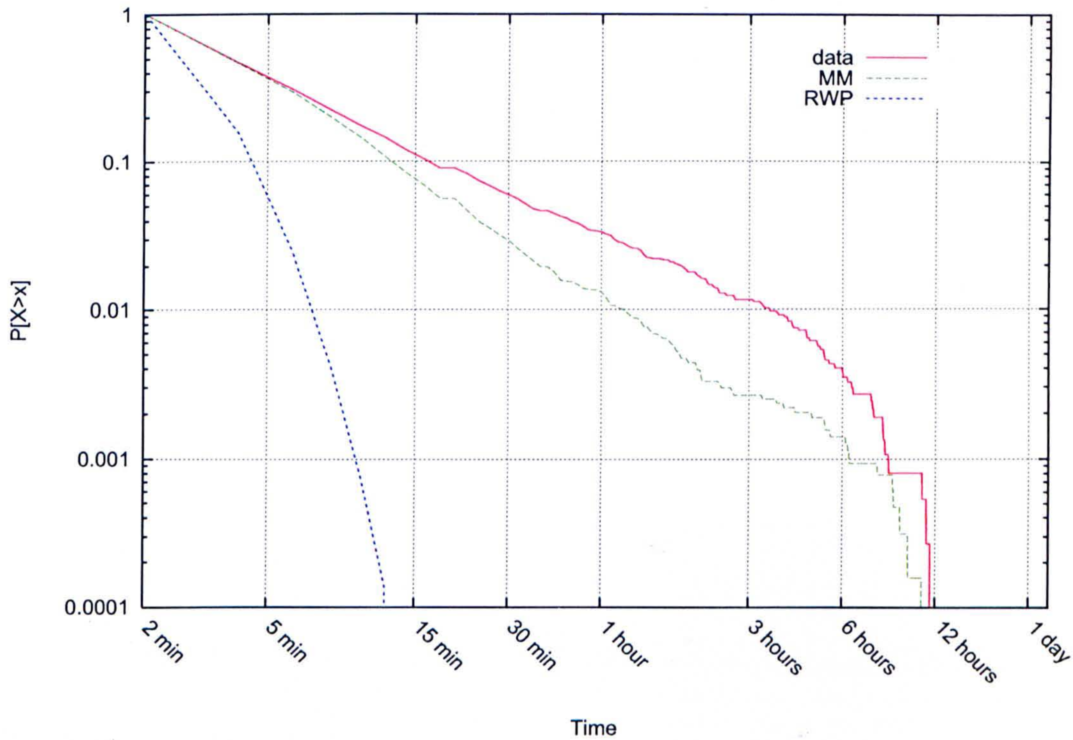

Figure 4.19: Contact Time distributions over six days between the internal fixed node "7398" and all the individuals resulting from real traces (data), our shopping mall mobility model (MM), and the Random Way-Point mobility model (RWP).

situation from the real shopping mall and have shown that our mobility model consistently approximates the inter-contact time and contact duration distributions from the real traces, while the Random Way-Point model does not.

Although we do not have logs from customers' devices in order to directly compare inter-customer contacts, the results from inter-seller and seller-to-contacts imply that the customers' movement is realistic.

In the next chapter we compare the performance of two different delay tolerant routing protocols against four different mobility models, including our shopping mall model. This allow us to see how different mobility models affect the performance of routing protocols.

Chapter 5

Testing and Evaluation of Different Routing Protocols

Although nature commences with reason and ends in experience
it is necessary for us to do the opposite,
that is to commence with experience
and from this to proceed to investigate the reason.

Leonardo da Vinci

Evaluation of performance of network applications and protocols in mobile ad-hoc delay tolerant networks is usually based on simulations. Such simulations rely on mobility models because these have a major influence on the performance of routing protocols.

In this chapter we explore how the delivery performance of two contrasting delay tolerant routing protocols differs with different mobility models. We evaluate Epidemic [18] and

Prophet [54] routing protocols in terms of large-scale performance.

In our simulations we test the Epidemic and Prophet routing protocols with four distinct mobility models: Random Walk, Random Way-Point with inter-arrival time, Random Walk with with inter-arrival time and the Shopping Mall mobility model. All of these are described in the Chapter 3 and generated by our scenario generation tool with the three provided configurations, respectively `SimplestRWP`, `RandomWayPoint` and `MallMotion`. We include the Random Walk and Random Way-Point models with inter-arrival time to allow us to separate out the effects of a changing customer population from the additional structure of the Shopping Mall mobility model.

In addition, we evaluate two semi-Epidemic routing protocols running on our Shopping Mall mobility model. These are identical to the Epidemic protocol except that they forward messages exclusively to customers or sellers at intermediate hops. This allows us to expose differences in forwarding data throughout customers versus sellers in such environments.

We begin by briefly reviewing some established routing protocols for mobile ad-hoc and delay-tolerant networks. We then describe the simulation settings before discussing the results that we have obtained.

5.1 Related Work

In this section we present a description of the comparisons of various mobility models. All of them analyse the impact of different mobility models on the performance of some routing protocols.

Camp et al. [35] considered various synthetic mobility models and discussed the importance of choosing an appropriate mobility model for the performance evaluation of a given ad hoc network protocol. They compared the results of four different mobility models with DSR routing protocols [135]. They considered the data packet delivery ratio, the end-to-end delay, the average hop count, and the protocol overhead.

Ravikiran et al. [136] considered theree mobility models, Pursue, Column and Reference Point Group Mobility (they are described in [35]) and compared the effects of these mobility models on the performance of three ad hoc routing protocols, AODV [137], DSDV [138] and DSR. In [139] McNeill et al. compared the simulation results of AODV, DSR, and TORA [140] with the Random Way-Point, Random Walk and Pursue mobility models varying the mobility speed and the pause time.

A comparison of the Random Way-Point and the Gauss-Markov mobility model is presented in [141] and the effects of three random mobility models, Random Way-Point, Random Walk with Reflections and Random Walk with Wrapping, on the performance of AODV are in [142]. The results shows that performance of the routing protocol varies across different parameters like number of nodes, packet delivery ratio and end to end delay. An analysis of the effects of four mobility models, Random Wayward mobility, Group Mobility, Freeway and Manhattan mobility models, on the performance of two routing protocols, DSR and DSDV, is presented in [143].

Gowrishankar et al. [144] studied the performance of various group mobility models like Community model, Group Force Mobility Model, Reference Point Group Mobility, a pseudo group mobility model like Manhattan model and a random mobility model like Random Waypoint-Steady State with AODV routing protocol. Here, various metrics like packet delivery ratio, average network delay, network throughput, routing overhead and number of hops have been considered.

The above mentioned works prove that the performance of an ad hoc network protocol can vary significantly with different mobility models. The performance of a delay tolerant network protocol or application should be evaluated with the mobility model that most closely matches the expected real-world scenario. The authors analysed the performance of several mobility models considering nodes' mobility. They compared the simulation results of various synthetic mobility models on the performance of some ad hoc routing protocols. Here, we have considered four mobility models with different nodes' mobility, Random Walk, Random Way-Point with inter-arrival time, Random Walk with with inter-arrival time and the Shopping Mall mobility model, and have compared the effects of these mobility models on the performance of two delay tolerant routing protocols, Epidemic and Prophet.

5.2 Metrics for Evaluating Forwarding Efficiency

In this chapter we analyse the performance of benchmark delay tolerant routing protocols, Epidemic, Prophet, and a derivative of the former, with different mobility models. The aim of this evaluation approach is threefold. First, they will eventually provide evidence that traditional mobility models should not be employed to simulate "structured" scenarios. Second, the choice of a mobility model can be a critical consideration when designing and evaluating routing protocols for shopping mall environments. Finally, it will allow us to gain better understanding of the potential role of message carriers belonging to groups with different mobility patterns. We note that the performance of the Epidemic protocol is strictly correlated to the connectedness of end-to-end paths with hosts with infinite buffer capacity.

In our simulations we tested routing protocols with four distinct mobility models going from a pure random-based to a more realistic Shopping Mall mobility model. The first three are Random Walk-based mobility models. We chose them as Random Walk-based because such a model is the most commonly used mobility model by the research community to simulate several scenarios for mobile networks [35, 135, 145, 146, 147]. They are all characterized by nodes' mobility with different degrees of freedom to move respect to time and space. Decreasing spatial mobility and speed, and increasing pause time reduces the degree of freedom of nodes. The first scenario represents a pure Random Walk. The second and third scenarios are a Random Way-Point and a Random Walk mobility model with inter-arrival time respectively. The first three mobility models describe scenarios without obstacles where all of the nodes can move as they like within the shopping mall area. The fourth scenario is generated by our shopping mall mobility model. In the last three scenarios the number of nodes in the simulation area varies with the time because of their entering and leaving the shopping mall. Nonetheless, the number of nodes is reasonably constant over time. In the last two scenarios, nodes can move with lower speed and have pause time. Besides, the fourth scenario reproduces the plan of a shopping mall (the one in Figure 2.1) as playground with obstacles, shops and corridors where nodes can move.

In the majority of the work presented in Section 5.1, delivery ratio and average delay have been used as metrics to evaluate the network performance.

- **Delivery Ratio**

  Excessive data traffic often impacts on the performance of routing protocols and on the data delivery when network link capacity is limited. Delivery ratio expresses the *efficiency* of routing protocols. It is given by the number of messages received over the total number of messages sent. Its value provides a theoretical delivery ratio upper bound when the buffer size is infinite as well as an estimation of the number of hosts in the same connected component of the resulting network path.

- **Average Delay**

  Delay is the amount of time it takes for data to travel from one node to another across a network. Their statistical measures such as mean, variance, empirical distributions, are important and provide an assessment of *effectiveness* of a routing protocol. Average delay is calculated as the average time between the generation of the message and the delivery to the final recipient of the message. It is a characterising aspect of a protocol for delay tolerant mobile networks.

In this thesis, I will limit my evaluation to delivery ratio and average delay for all the simulations conducted to compare forwarding efficiency and effectiveness in a network where all connectivity is short-range wireless.

5.3 Routing Protocols

In this thesis we are considering a large population of wireless computing devices in a specific environment wishing to communicate without exploiting fixed infrastructure. While traditional networks rely on infrastructure to provide connectivity to mobile wireless devices, in our context we focus on networks that use only a shared wireless medium. In these kind of networks an end-to-end communication cannot always be ensured and disconnections can occur due to host mobility in particular. Mobile ad-hoc networks assume an existing end-to-end path between nodes wishing to communicate whereas in delay tolerant networks this is not always the case. Routing protocols in both networks might cope with challenges such as host mobility/dynamics, potentially very large number of hosts, and limited communication resources (e.g. bandwidth, memory capacity and energy consumption). They may have to adapt quickly to frequent and often unpredictable topology changes and must be parsimonious of network resources. In such networks scalability can be important, and has been attracting increasing attention.

Different network structures engender distinct approaches to scalability which consequently affect the design and operation of routing protocols. In some application domains, scalability is achieved by designing a hierarchical architecture with physically distinct layers. While for infrastructure networks a hierarchical structure is assigned a priori, in delay tolerant and mobile ad hoc networks scalability must take into account a node's distinctive characteristics, e.g. mobility pattern, energy consumption, processing power, buffer capacity. Achieving a highly scalable mobile network is difficult. Nonetheless, in the case of the shopping mall we have identified two classes of individuals with different mobility patterns which might contribute to the design of a suitable network structure for this kind of scenario (see Section 2.5).

We now review some of the well-known routing protocols for mobile ad-hoc networks and delay tolerant networks.

5.3.1 Mobile Ad-Hoc Networking

The design of network protocols for mobile ad hoc networks is a complex issue [24]. Issues that the IETF (Internet Engineering Task Force) MANet working group [148] has considered [25] include: efficient routing of packets; methods to conserve energy at nodes; and mobility pattern of nodes are some. The routing protocols proposed to date are usually classified in three main classes: proactive, reactive and hybrid protocols.

Routing protocols that periodically and continuously update routes in the network are named proactive. Typically, each node regularly floods the network with link information about its neighbours. Because of this, packets can be forwarded immediately as the route to the destination is already known. Destination-Sequenced Distance Vector routing protocol (DSDV) [138], Wireless Routing Protocol (WRP) [149], Global State Routing (GSR) [150], Fisheye State Routing (FSR) [151], Fuzzy Sighted Link State (FSLS) [152], Optimized Link State Routing (OLSR) [153] and Topology Broadcast Based on Reverse Path Forwarding (TBRPF) [154, 155] are examples of proactive protocols. Unfortunately, in large scale mobile networks, such protocols generate a higher routing control overhead which can overload the network and lead to consequent disruptions.

Reactive protocols are routing algorithms that initiate a route discovery process only on-demand. If a source node requires a route to the destination then it floods the network with query packets in search of a path. The process ends when a route is found or all possible paths are searched. There are different approaches to route discovery in reactive protocols. Some of the well known on-demand protocols are Ad-hoc On-demand Distance Vector (AODV) [137], Associativity-Based Routing (ABR) [156], Dynamic Source Routing (DSR) [135], Lightweight Mobile Routing (LMR) [157], Signal Stability-based Routing (SSR) [158], and Temporally Ordered Routing Algorithms (TORA) [140]. Among the above-mentioned reactive protocols, AODV and DSR have received major attention by researchers [159, 107, 160]. However, in mobile networks, reactive protocols generally suffer from slow route convergence and routing loops.

Finally, hybrid protocols combine proactive and reactive routing strategies and can combine the benefits of both. Some hybrid routing protocols such as Zone Routing Protocol (ZRP) [161, 162, 163], Landmark Ad Hoc Routing Protocol (LANMAR) [164, 165], Location Aided Routing (LAR) [166], and Distance Routing Effect Algorithm for Mobility (DREAM) [167] use landmarks, location and distance from nodes to reduce routing control overhead.

Routing algorithms for mobile ad-hoc networks assume that there is always a connected path from source to destination. Thus, such protocols cannot be employed for partially connected ad hoc networks.

5.3.2 Delay Tolerant Networking

With the advent of short-range wireless communication technologies such as IEEE 802.11 [168], Bluetooth [169], and IEEE 802.15 [170] and the growing diversity of applications, mobile ah-hoc networking assumptions are not always valid in realistic scenarios. Several approaches have been proposed to enable communication in such intermittently connected networks. In [4] Fall proposes a Delay Tolerant Network architecture which aims to provide interoperable communications between a wide range of networks which may have exceptionally poor and disparate performance characteristics. Within this general architecture several different approaches can be used for routing, which are distinguished by what (if any) information they use to make forwarding decisions and the extent to which messages are duplicated within these networks.

Flooding Based Approaches

In [171] Jain et al. state that knowledge about the network helps in deciding the best next hop. If nodes do not have any knowledge of network resources they will all act as relays. This behaviour pattern is called Epidemic routing. The idea is to flood the network, like a virus spreading in an epidemic. This is the simplest way of enabling communication in intermittently connected networks, by replicating messages to all the nodes that do not have a copy of it already (or to a certain number of them in semi-epidemic algorithms) .

Vahdat and Becker, inspired by the algorithms proposed by Demers et al. [172] which attempt to guarantee data consistency after disconnections in distributed database systems, presented the Epidemic routing protocol [18]. It is a milestone for much of the work in this field, even though it does not consider issues such as overuse of buffer, bandwidth, and energy consumption which can seriously degrade the network performance [173].

Several approaches derived from Epidemic have been proposed with the intention of controlling flooding and saving resources. Some of them try to limit the number of copies in the network by means of the single-copy routing scheme [174, 72, 175]. One-hop or two-hop relay routing only permit data to be transmitted in one or two hops respectively [176, 177], and the Spray and Wait algorithm [178] is similarly limited.

Though these approaches improve the delivery ratio, they do not take into account the buffer size. Therefore, further solutions suggest saving buffer space by limiting the life time of each message copy [179] or controlling some network parameters [180, 181, 182]. Other flooding technique conserve network resources by embedding additional information in the message to limit the number of copies in the network as a whole [183, 184, 185, 186].

History Based Approaches

History based routing protocols take into account the history of encounters between nodes when forwarding messages. The main idea behind these approaches is that a node frequently in contact with the destination has a higher probability of encountering the destination again. Jain et al. [171] state that in situations where resources are limited (e.g. contact opportunities, bandwidth or storage) smarter algorithms may provide a significant benefit. They developed a framework for evaluating DTN routing algorithms, and suggested and evaluated several algorithms based on the Dijkstra's algorithm and on a partial or total knowledge of the time-varying network topology through an oracle.

Lindgreen et al. [54] propose the PROPHET routing protocol, a PRObabilistic Protocol using History of Encounters and Transitivity. PROPHET considers knowledge about previous encounters between nodes in order to calculates a delivery probability for each node encountered and chooses as foster node the node that expresses higher probability. The delivery probability is decreased by means of an "estrangement" factor if two nodes have not encountered each other for a certain time period. Consequently, if node A encounters nodes B and C more frequently than they encounter each other, then A can be used as relay for the communication between B and C.

The NECTAR [187] protocol creates a neighbourhood index, which is used to determine the most appropriate route, by means of contact history. Simulations performed with real data retrieved from mobile and wireless environments at Dartmouth College [188], a scenarios where the occurrence of highly-partitioned networks is frequent, show that NEC-

TAR is able to deliver more messages than Epidemic and PROPHET protocols with lower consumption of network resources.

The MaxProp [189] is a routing protocol for vehicle-based disruption-tolerant networks. It prioritizes both the schedule of packets transmitted to other peers and the schedule of packets to be dropped. The priority policy is based on the path likelihoods to peers according to historical data and on several complementary mechanisms.

The protocols introduced so far consider history of previous contacts to route data. Some other protocols use context information. CAR (Context-aware Adaptive Routing) [190] is an approach to delay-tolerant mobile ad hoc network routing that uses a Kalman Filter for prediction and multicriteria decision theory [191] to choose the best next hop (or carrier) to forward the message. Another protocol based on context information is MobySpace [192] [193]. It evaluates routing in a virtual space defined by the mobility patterns of nodes. ORWAR [194] is a resource-efficient protocol for opportunistic routing in delay-tolerant networks which exploits the context of mobile nodes, namely, speed, direction of movement and radio range, to estimate the size of a contact window and choose better forwarding decisions. EASE (Exponential Age SEarch) [195, 196] is a context-based routing protocol based on the assumption that in a model where N nodes perform independent random walks on a square lattice, the length of the routes computed by EASE are on the same order as the distance between the source and destination.

5.3.3 Routing Protocols Used in the Simulations

In order to show how mobility models impact on the performance of routing protocols we selected two well-known routing protocols, Epidemic and Prophet, on the mobility models mentioned in the previous section. We chose Epidemic and Prophet because they are often used as benchmark routing protocols in simulations carried out by the delay tolerant network research community. In addition, Epidemic provides a theoretical upper bound in terms of delivery ratio when the buffer size is infinite.

Epidemic is a resource hungry protocol because it does not use any knowledge of the system to forward messages. This is a flooding-based approach and is particularly efficient if hosts' movement is purely random. But in realistic scenarios human mobility is rarely completely random. Prophet, in contrast, tries to exploit the non-randomness of individuals' encounters by maintaining a list of delivery probabilities for known destinations. This presume that human mobility is often goal-oriented and that encounters could be predictable.

In addition, we conducted further analysis by evaluating the performance of two semi-Epidemic protocols with our Shopping Mall mobility model. We refactored the Epidemic algorithm without modifying its main functional behaviour in order to build two semi-Epidemic protocols. These are identical to the Epidemic protocol except that they forward messages exclusively to customers or sellers at the intermediate hops. The functionality that has been added to the semi-Epidemic protocols is the capacity to distinguish between customers and sellers by simply reading their identification number. They simply "flood" the network either through customers or through sellers. In our simulations, nodes with the identification number between 1 and 45 are shop employees. By comparing these simulation results we aim to expose differences in forwarding data through customers versus sellers in such environments.

5.4 Simulation Scenarios

We consider a shopping mall simulation scenario based on four different mobility models. The movement traces of the simulated hosts were generated using our mobility model generation tool presented in Chapter 3. All the scenarios have in common 45 sellers (the actual number of sellers in the mall) and a simulation area of $10,880m^2$ (the size of the actual shopping mall).

In our simulations we test such routing protocols with four distinct mobility models going from a pure random-based to a more realistic Shopping Mall mobility model. We chose Random Walk-based mobility models because they have been often employed by the research community to simulate several scenarios for mobile networks [35, 135, 145, 146, 147]. We employed four distinct mobility models characterized by different degrees of freedom for nodes to move respect to time and space. Decreasing spatial mobility and speed and increasing pause time reduces the degree of freedom of nodes. Fixed nodes are not considered for these simulations.

In the first scenario, which represents a Random Walk mobility model, the same 225 nodes were always present (see Figure 3.2). This is the sum of 45 sellers and the arithmetic mean calculated on a sample of one hundred recordings of the number of customers in the shopping centre after two hours[1] following the inter-arrival time cumulative distribution function (from Section 3.5.2) and a random number generator. Notice that this is the number of individuals carrying an active Bluetooth device; people might turn Bluetooth appliances off if not needed or to save battery power. The following command line (5.1) generates this first scenario with constant speed of $1.65m/s$ and duration equal to 12 hours.

```
MM -f scenario SimplestRWP Simple.svg -d 43200 -i 3600 -h 1.65 -l 1.65 -p 0
```

(5.1)

The other three scenarios make use of two cumulative distributions to describe the customers' inter-arrival time and their staying time in the mall. These distributions are the same for each scenario and were extracted from our real traces (see Section 3.5.2). The distribution functions and their parameters are (5.5) and (5.8) from the list below. Because these are random processes, the number of customers in the simulation is not constant, but varies according to the distributions.

The second and third scenarios are a Random Walk and Random Way-Point mobility model respectively. The command lines that generate twelve hours of each scenario are the following:

[1]After two hours the system is in a steady state; the average number of customers in the mall falls within a certain range, namely the probability of customers leaving the mall is equal to their arrivals

```
MM -f scenario RandomWayPoint RWP.svg -d 43200 -i 3600 -h 1.65 -l 1.65 -p 0
```
(5.2)

```
MM -f scenario RandomWayPoint RWP.svg -d 43200 -i 3600 -h 1.65 -l 1.15 -p 2
```
(5.3)

The command line (5.2) generates a Random Walk with constant speed of $1.65m/s$. A node's speed in this scenario is equal to the highest permitted speed in the previous one. The command line (5.3) uses a Random Way-Point model with speed in the range $[1.65 - 1.15]m/s$ and a maximum pause time of $2s$ as in Chapter 4 (see Section 4.3). The three mobility models introduced so far in this section describe scenarios without obstacles where all of the nodes can move as they like within the shopping mall area.

The fourth scenario is generated by our Shopping Mall mobility model. This mobility model considers obstacles as well as shops, stores, rooms, walls, and paths (see Section 3.3 and Figure 3.4). The command line to reproduce a shopping mall scenario is the following:

```
MM -f scenario MallMotion drawing.svg -d 43200 -i 3600 -h 1.65 -l 1.15 -p 2
```
(5.4)

The above line 5.4 generates twelve hours of simulation with nodes' speed in the range $[1.65 - 1.15]m/s$ and a maximum pause time of $2s$. These parameters are equal to those used in the third scenario (command line (5.3)).

Furthermore, as described in Section 3, our scenario generation tool needs three more cumulative distribution functions respect to the previous two models to generate this last scenario. Like the previous two, these distributions are extracted from our data set (see

Section 3.5). The distributions together with their respective parameters are the following:

$$\texttt{iat} \; : \; \texttt{exp(rate=1.771467e-03)} \tag{5.5}$$

$$\texttt{stay(sellers,shop)} \; : \; \texttt{lnorm(meanlog=7.08653949,sdlog=1.87655822)} \tag{5.6}$$

$$\texttt{stay(sellers,!shop)} \; : \; \texttt{lnorm(meanlog=6.50409971,sdlog=0.51007676)} \tag{5.7}$$

$$\texttt{stay(customers,mall)} \; : \; \texttt{weibull(shape=9.3573e-01,scale=2.5797e+03)} \tag{5.8}$$

$$\texttt{stay(customers,shop)} \; : \; \texttt{weibull(shape=1.0028e+00,scale=3.0595e+02)} \tag{5.9}$$

5.5 Simulation Tool and Setting

The code of the Epidemic and Prophet protocols have been provided by Dr. Mirco Musolesi and Dr. Cecilia Mascolo. These protocols have been implemented for the work in [190] and follow respectively the descriptions presented in [18] and [54]. The values of the parameters of Prophet are those suggested by the authors in their paper [54]. We modified the code to work with our mobility models and simulation playgrounds.

In contrast to Section 4.3, here we consider the mobile scenario at the network level and do not consider issues related to Physical and MAC layers such as packet loss, collision or signal fading and do not deal with retransmission of packets. Such issues are not discussed in this work of thesis since these are secondary aspects of our problem. Being in reach is the primary matter of our study in this chapter. We assume that two devices can simply transmit messages when they are in radio range. Consequently, we do not model retransmission of packets. Unlike in Chapter 4 where we chose Physical and Link layer parameters as close as possible to the field trial settings, in this study we can neglect such a level of detail. Here, we provide a basic comparison of routing protocols with a reasonable approximation and slightly optimistic results. Nonetheless, this is sufficient for the purpose of this initial study, apart from producing much faster simulations.

All of the protocols being simulated rely on the assumption of pairwise connectivity, namely two nodes can communicate when they are within each other's radio range. They use summary vectors that index the list of messages stored at each node to mutually find out which messages can be obtained from each other. Each message is identified by a unique message identifier.

Table 5.1: Simulation parameters for all the scenarios

Propagation model	free space
Antenna type	*omnidirectional*
Transmission range	$30m$
Number of messages sent	1000
Max number of hops	1000
Message retransmission interval	$134s$
Buffer size	100

In our simulations, we use values for the parameters generally adopted in the literature[2]. Table 5.1 summarizes the simulation parameters used for all the scenarios. Such parameters are defined in the configuration file `omnetpp.ini`. It tells the simulation program which network will be simulated, and contains values for the parameters of the models employed and settings that control the simulation execution. We used the same configuration file for the Epidemic, Prophet and the two semi-Epidemic routing protocols. This is shown in the Appendix I.1.

With respect to the radio technology, we also assumed a free space propagation model with all the nodes having a transmission range of 30 metres and the use of omnidirectional antennas as in Section 4.3. The retransmission interval was 134 seconds. These settings are the same as those used by the Bluetooth appliances of our smart phones employed in the field trial to collect contact data in the shopping mall (see Section 2.3).

[2]Unfortunately, the choice of values for parameters of simulations for ad hoc networks research is extremely variable. In general, results published on mobile ad-hoc and delay tolerant network simulation studies lack credibility in terms of consistent scenarios to validate and to benchmark the different solutions. Kurkoswski et al. [197] have identified several pitfalls throughout the simulation lifecycle, by analysing the performance evaluation of papers published at MobiHoc from 2000 to 2005, which take away from the goals of making the research repeatable, unbiased, rigorous, and statistically accurate. We would like to underline that in this work, we have tried to address the shortfalls that are usually pointed out by the members of the community, such as the problem of the repeatability of the experiments (the code of our simulations will be released for comparisons), the use of a reasonable number of runs of experiments to ensure statistical validity to the results, the definition of confidence intervals and a thorough sensitivity analysis, considering a large number of different mobility traces.

We assumed a buffer size equal to 100 slots, i.e. whose capacity is 10% of the number of messages sent in the network. We assume that each host is able to store one message per slot. No messages were sent for the first 7200 seconds, in order to allow the simulation scenario to converge to a steady state, for example, a typical number of customers in the mall. We evaluated the performance of each routing protocol by sending 1000 messages over a simulation time equal to 2400 seconds. The minimum interval between the generation of two subsequent messages is equal to 0.1 seconds, as long as the chosen recipient node is different from the sender. In other words, the generation of all the messages will take at least 100 seconds. In our network scenario, with the settings listed in Table 5.1, the generation of messages with such a frequency produces a certain network load which will stress the network itself and allows network protocols to show better the capability of network protocols in routing data. The sender and recipient of each message were randomly chosen among all of the nodes in the mall following a uniform distribution. Thus, it might happen that they are about to leave the mall and unable to deliver their messages. This choice may be unrealistic[3], however, it is clearly less optimistic than assuming that communication happens only between people just arrived at the shopping mall. We run equal number of simulations with each combination of customers and sellers as senders and receivers: i.e. the number of runs was 50 for each combination of each scenario. This was sufficient to determine a 95% confidence interval using a t-distribution.

The structure of the simulation models for the above-mentioned routing protocols are described by the `NED` syntax through the `epidemic.ned` and `prophet.ned`. `NED` (NEtwork Description) is the network topology description language of Omnet++. The same `NED` structure has been used to run the Epidemic, Prophet and the two semi-Epidemic routing protocols. This is presented in the Appendix J.1.

[3]The main problem in designing realistic traffic models for delay tolerant networks is the lack of real data for validating it, especially for shopping mall environments

5.6 Simulation Results

In this section we present simulations results which show the impact of different mobility models on the performance of the above-mentioned routing protocols in the mall-based scenarios. We present these results in terms of message delivery ratio and average delivery delay. The former is given by the ratio between the number of messages received and the total number of messages sent. The average delay is the arithmetic mean of all times between the generation of the message and the delivery to the recipient of the message divided by the number of values. We have used boxplots to display the simulation results as they are valuable tools for explanatory data analysis. The boxplot is read as follows:

- the upper and the lower edge of the box respectively identify the 75th and the 25th percentile,
- the horizontal line in the box shows the median[4] value of the data,
- the vertical line links up the maximum and the minimum data values,
- any point shown outside the box the vertical line are outliers.

5.6.1 Impact of Mobility Models

Here, we analyze the impact of different mobility models on the performance of the Epidemic and Prophet routing protocols. The mobility models, described in Section 5.4, are identified in the plots with the following order and with the respective labels:

- `rw`: Random Walk,
- `irw`: Random Walk with Inter-arrival time,
- `irwp`: Random Way-Point with Inter-arrival time,
- `sm`: Shopping Mall.

[4]If the median line within the box is not equidistant from the upper and lower hedges, then the data distribution is skewed

These are in order of decreasing degree of freedom of nodes: `rw` and `irw` use a constant (maximum) node speed without pauses, `irwp` uses speeds between an upper and lower bound and non-zero pause time while `sm` divides the simulation area in smaller spaces representing the shopping mall. In all cases, the maximum node speed is $1.65m/s$ while `irwp` and `sm` have a possible minimum speed of $1.15m/s$ and a random pause time of up to $2s$ after each movement (see Section 5.4).

Initially we run simulations distinguishing between customers and sellers to be selected as sender and recipient, namely, from customer to customer, customer to seller, seller to customer and seller to seller. Their respective graphs are in the Appendices K.1, K.2, L.1 and L.2. Here we unify these results and show them together in a single plot.

The first two plots in Figure 5.1 and 5.2 show respectively the delivery ratio and the average delay using the Epidemic protocol. In Figure 5.1 we observe that the delivery ratio decreases with the decreasing degree of freedom of the scenarios. This is in accordance with Grossglauser and Tse [72] who claim that mobility increases the capacity of ad hoc wireless networks. Their results suggest that delay-tolerant applications can take advantage of node mobility to significantly increase the throughput of such networks. As regards the average delay of the message to reach the final destination, Epidemic has a slightly higher mean with the traditional Random Walk mobility model while the other three mobility models produce roughly the same mean but with large range of minimum delay. This is because in the Random Walk case all of the nodes are independent and identically distributed in the mall area and so have the same probability for their messages to reach any recipient with the same average delay.

Like Epidemic, in Figure 5.3 Prophet also shows decreasing mean delivery ratio with scenario, with the exception of the Shopping Mall mobility model, where it performs better than `irw` and `irwp`. This is explained by Prophet's exploitation of the non-randomness of individuals' encounters. Human mobility and encounters in structured environments like shopping malls is likely to be more predictable than in unconstrained scenarios. Recall that the `rw` model does not consider inter-arrival times which are likely to negatively impact the

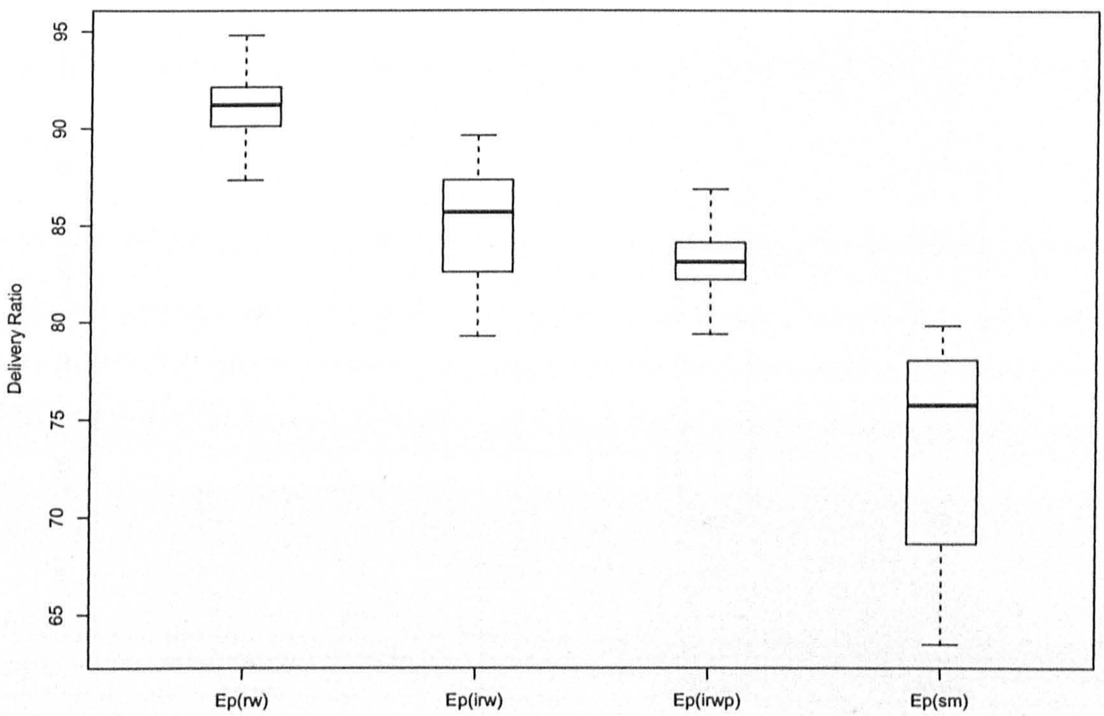

Figure 5.1: Boxplot of the delivery ratio for the Epidemic routing protocol with the Random Walk (`rw`), Random Walk with inter-arrival time (`irw`), Random Way-Point with inter-arrival time (`irwp`) and the Shopping Mall (`sm`) mobility model.

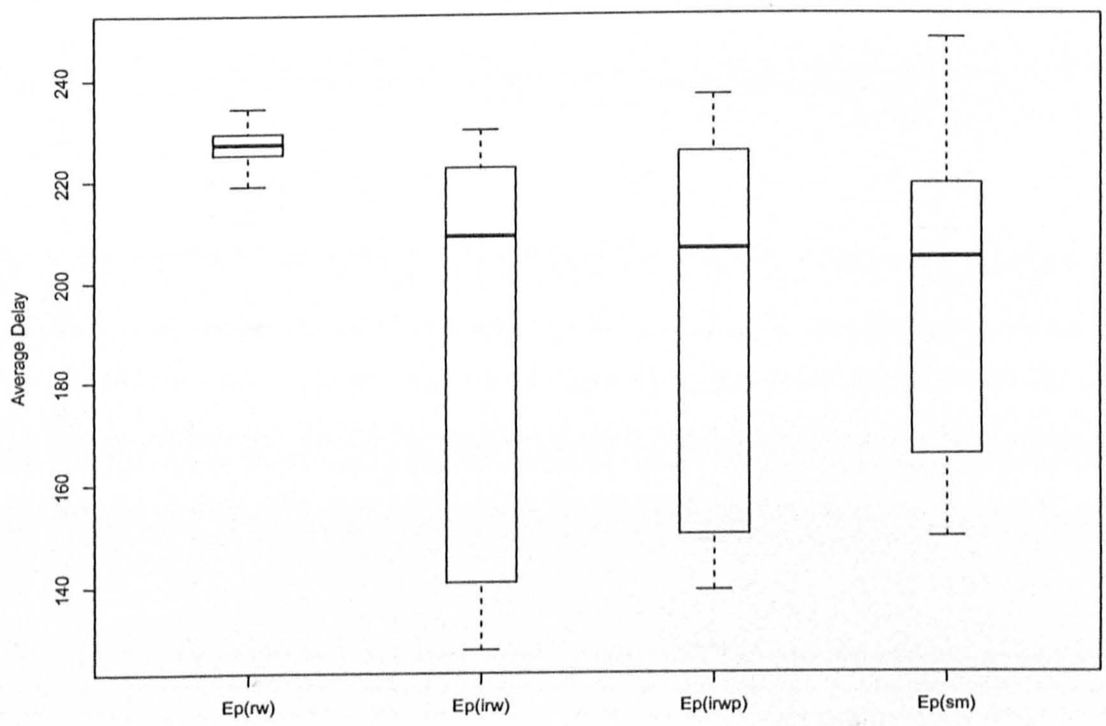

Figure 5.2: Boxplot of the average delay for the Epidemic routing protocol with the Random Walk (`rw`), Random Walk with inter-arrival time (`irw`), Random Way-Point with inter-arrival time (`irwp`) and the Shopping Mall (`sm`) mobility model.

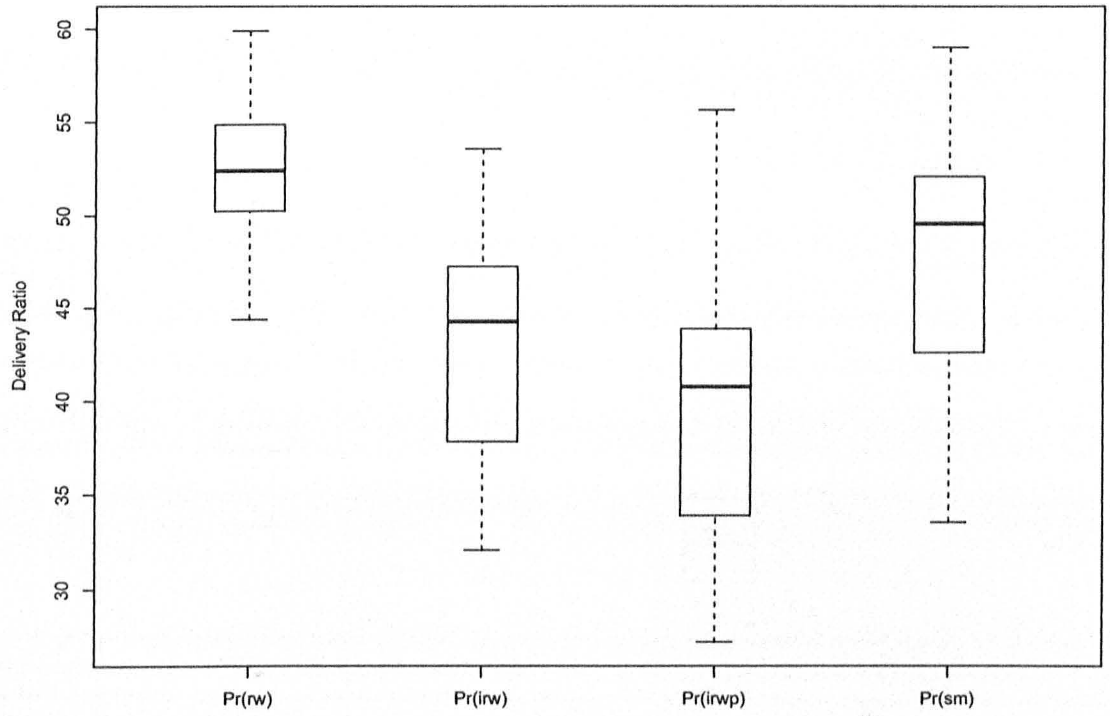

Figure 5.3: Boxplot of the delivery ratio for the Prophet routing protocol with the Random Walk (`rw`), Random Walk with inter-arrival time (`irw`), Random Way-Point with inter-arrival time (`irwp`) and the Shopping Mall (`sm`) mobility model.

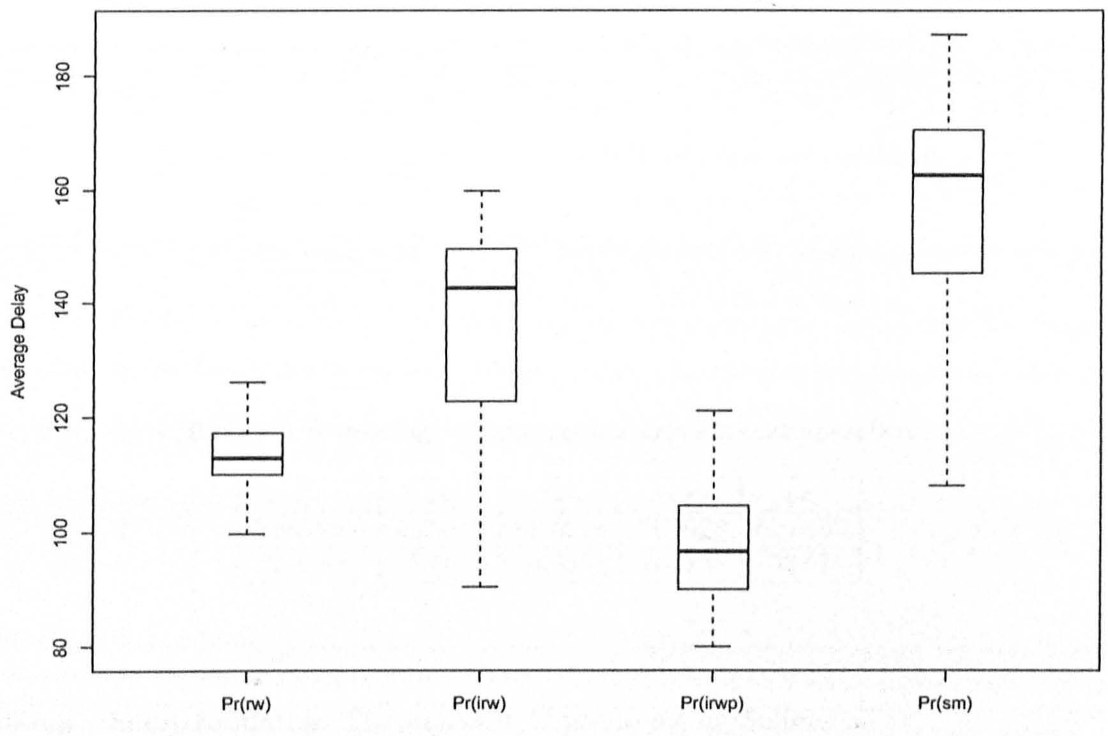

Figure 5.4: Boxplot of the average delay for the Prophet routing protocol with the Random Walk (`rw`), Random Walk with inter-arrival time (`irw`), Random Way-Point with inter-arrival time (`irwp`) and the Shopping Mall (`sm`) mobility model.

outcome of the simulations. Figure 5.4 shows the average delay for delivering messages with Prophet. Here, `sm` has the longest average delay.

In Tables 5.2 and 5.3 we show the probabilities for messages to reach recipients by exploiting customers or sellers as intermediate carriers. Unlike Epidemic, Prophet tends to forward messages to customers as intermediate carriers. This may be because customers have a higher degree of freedom than sellers, and are also greater in number. Consequently, they may be in contact with more individuals and therefore more reliable as intermediate carriers of messages. This may contribute to the longer delays observed with the `sm` model.

Table 5.2: Percentage of intermediate carriers that are customers

%	`rw`	`irw`	`irwp`	`sm`
Epidemic	56.6486	31.9982	28.3077	47.0818
Prophet	64.6323	63.9315	62.0142	67.43

Table 5.3: Percentage of intermediate carriers that are sellers

%	`rw`	`irw`	`irwp`	`sm`
Epidemic	43.3514	68.0018	71.6923	52.9182
Prophet	35.3677	36.0685	37.9858	32.57

5.6.2 Semi-Epidemic Throughout Customers or Sellers

In this section we evaluate the performance of the two semi-Epidemic protocols described in Section 5.3.3 with our Shopping Mall mobility model. In the following plots we consider separately the four combinations of customers and sellers as sender and receiver for the two routing protocols. Combinations are identified in the figures using the following syntax:

$$\underbrace{\texttt{[C | S]}}_{\substack{\text{semi-Epidemic}\\ \text{protocol}}}\ (\ \underbrace{\texttt{[C | S]}}_{\text{sender}}\ \texttt{to}\ \underbrace{\texttt{[C | S]}}_{\text{receiver}}\ ) \qquad (5.10)$$

where the first field identifies whether the semi-Epidemic protocol forwards messages through customers `C` or sellers `S`. The combinations are summarized in Table 5.4.

Table 5.4: *Summary of configurations for the semi-Epidemic routing protocol simulations*

THROUGH	SENDER	RECEIVER	SYNTAX
Customers	Customer	Customer	`C(CtoC)`
Sellers	Customer	Customer	`S(CtoC)`
Customers	Customer	Seller	`C(CtoS)`
Sellers	Customer	Seller	`S(CtoS)`
Customers	Seller	Customer	`C(StoC)`
Sellers	Seller	Customer	`S(StoC)`
Customers	Seller	Seller	`C(StoS)`
Sellers	Seller	Seller	`S(StoS)`

The plots in Figures 5.5 and 5.6 show the performance of the semi-Epidemic routing protocols with two different buffer capacities. The white and the red boxes show the results when the buffer capacity of the nodes is 10% and 20%, respectively, of the number of the messages generated. As expected higher buffer capacities lead to high delivery ratios, and the impact of mobility model is similar in both buffer capacities.

The delivery ratio in the left part of Figure 5.5, that is `CtoC` and `CtoS`, is slightly higher if messages are delivered through sellers. In contrast, in the right part of Figure 5.5 messages routed through sellers result in lower delivery ratios. We conjecture that this is mainly because of the limited buffer capacity of each node and the different mobility pattern and relatively small number of sellers with respect to customers. Thus, the network becomes more overloaded when messages are generated by sellers and routed throughout them. This leads to buffer overflow and message loss. This is backed up by cases `S(StoC)` and `S(StoS)` where increasing buffer capacity has the biggest impact on the performance of the routing protocols. We believe that `C(CtoC)` and `C(CtoS)` show smaller delivery ratios than `S(CtoC)` and `S(CtoS)` because messages are generated by customers and forwarded to other customers who might be about to leave the shopping mall and not have time to forward them. On the other hand, sellers never leave the mall during their working time.

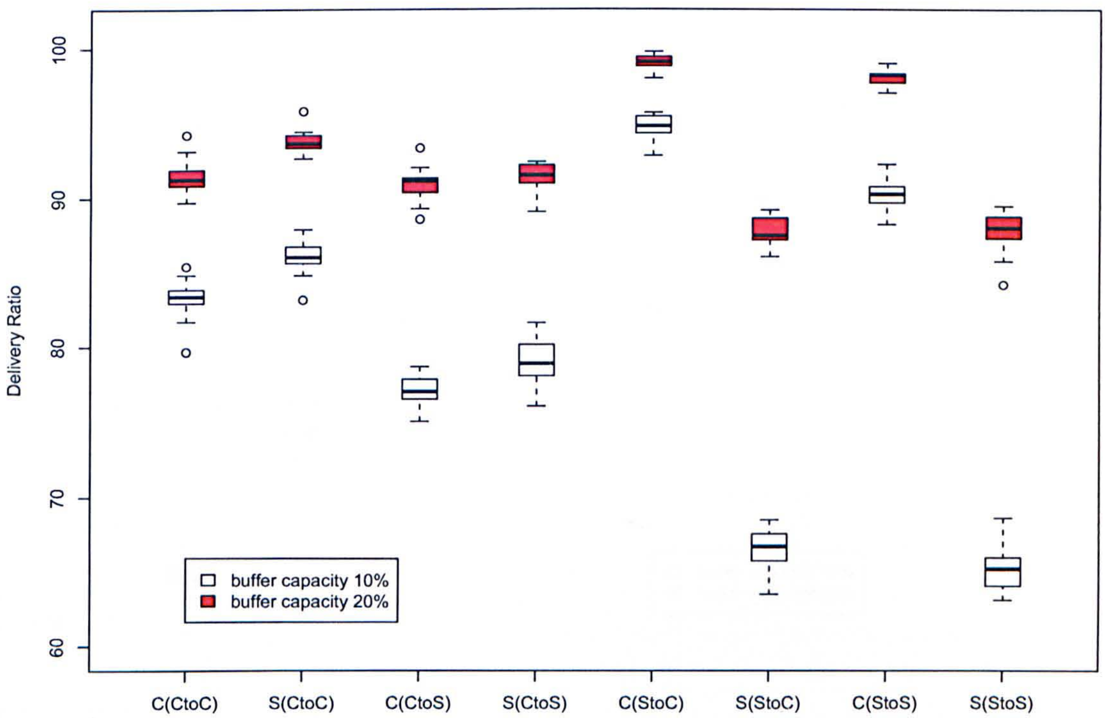

Figure 5.5: Boxplot of the delivery ratio for the semi-Epidemic routing protocols with the Shopping Mall (sm) mobility model.

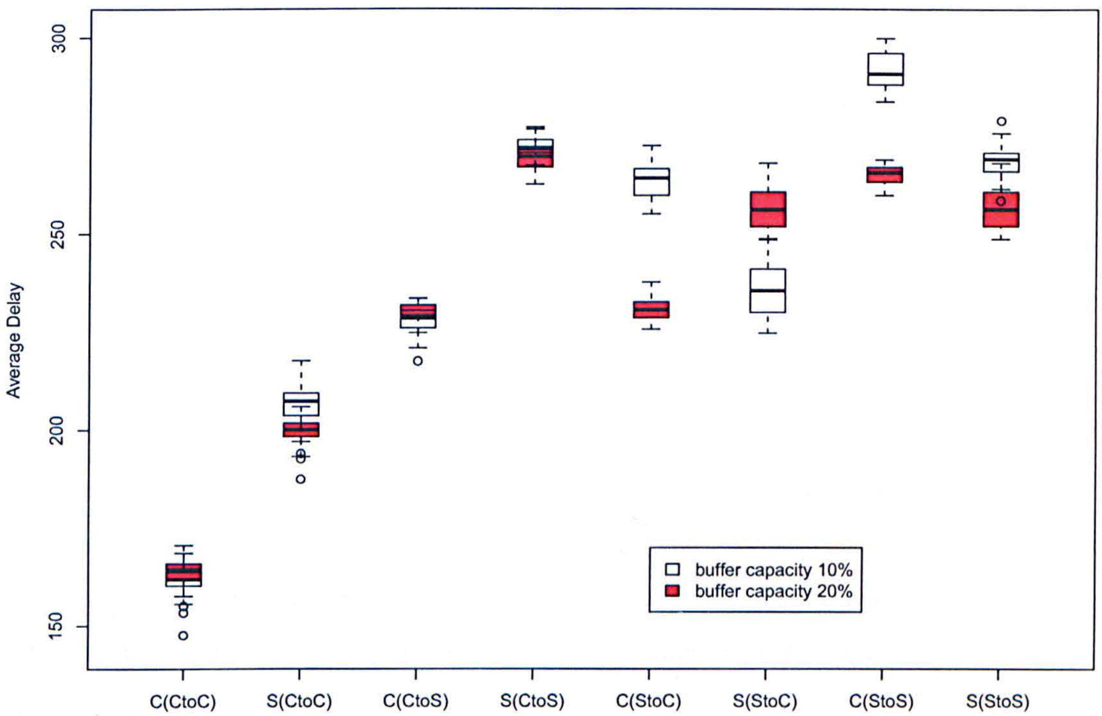

Figure 5.6: Boxplot of the average delay for the semi-Epidemic routing protocols with the Shopping Mall (sm) mobility model.

For the same sequence of cases the Figure 5.6 shows the average delay for delivering messages. Like delivery ratio in the previous figure this plot can be analysed in two parts. It seems that the average delay keep increasing following the combinations on the x-axis and as long as messages are generated by customers. These results are roughly the same for each buffer capacity. The average delay improves with bigger buffer capacity when senders and receivers are sellers. When messages are generated by sellers and received by customers, there is trade off between the type and number of intermediate carriers, customers or sellers, and their buffer capacity.

5.7 Summary

The main purposes of this chapter are threefold. First, we have shown that different mobility models impact on the performance of two benchmark delay tolerant routing protocols, Epidemic and Prophet, providing evidence that traditional mobility models should not be employed to simulate "structured" scenarios. Recall that the Epidemic protocol does not use any knowledge of the system to forward messages and is particularly efficient if hosts' movement is purely random. This is reflected in higher delivery ratios for mobility models with less structure and greater mobility. On the other hand Prophet tries to exploit the non-randomness of individuals' encounters. This is reflected in a relatively high delivery ratio with the shopping mall model, where Prophet is presumably able to exploit the structure to offset the reduced mobility of nodes.

Secondly, the same comparison shows that the choice of a mobility model can be a critical consideration when designing and evaluating routing protocols for delay-tolerant mobile ah-hoc networks. Here, for example, Prophet would have little apparent merit when tested with the first three (unstructured) mobility models. However, with the shopping mall model its merits begin to emerge.

Empirical results of previous work illustrate that the performance of a routing protocol varies significantly across different mobility models. The performance of routing protocols and applications in delay tolerant mobile ad hoc networks is greatly affected by the mobility model. Therefore, the performance of a delay tolerant network protocol or application should be evaluated with the mobility model that most closely matches the expected real-world scenario.

Third, we tested two semi-Epidemic routing protocols on our Shopping Mall mobility model, which forward data distinguishing between customers and sellers, to understand better the potential role of message carriers belonging to groups with different mobility patterns. As analysed in Chapter 2, sellers' mobility is mainly duty-bound to their shop, that is they have low degree of freedom, and are typically in contact with neighbouring sellers. These first simulation results show that forwarding messages through sellers rather than customers affects protocols performance. We conjecture that the choice of delivering data through customers rather than sellers depends on the resources available to hosts and when messages are generated. In particular, just considering buffer size, number of hosts and their mobility, if sellers had infinite buffer capacity, it might be better to route messages through sellers; otherwise customers could be preferable as they may be greater in number and more mobile. Thus, under particular circumstances it could be preferable forwarding messages to some carriers rather than others and thus information could be exploited in the design of routing protocols for delay-tolerant mobile ah-hoc networks in such environments.

Ideally, in the future, further investigations should be carried out. In our simulations, the performance of Epidemic as well as Prophet suffer due to the limitations of buffer size. It would be useful to investigate in more detail the impact of buffer size with these and other delay tolerant and mobile ad-hoc routing protocols. It would also be useful to explore larger scenarios in terms of simulation area and number of hosts involved, which might show greater differences and other distinctive characteristics. Furthermore, in the future we would like to design and evaluate forwarding algorithms for different pervasive applications in this type of settings.

Chapter 6

Conclusions

I am turned into a sort of machine
for observing facts and grinding out conclusions.

Charles Darwin

6.1 Summary of the Thesis

In this thesis we have recorded and analysed human mobility patterns in a shopping mall environment through a field trial lasting six days in a real shopping mall. We provided twenty-five smart phones to shopkeepers and clerks to collect contact data from Bluetooth devices and they all yielded valuable results. Their deployment was enough to continuously sense Bluetooth connectivity in more than half of the entire mall. This allowed us to analyse the collected contact traces and characterize human mobility in such environments.

We identified two main groups with different mobility patterns, customers and sellers, from the contact traces. For these two groups, we have observed and quantified mobility characteristics which could be taken into account to design forwarding algorithms and trace-based mobility models. Furthermore, out of such contact traces we extracted cumulative distribution functions describing the mobility behaviour of customers and sellers. Such distributions are important parameters for our Shopping Mall mobility model.

Building on this, we have presented the design and implementation of a mobility model generation tool and our Shopping Mall mobility model. Our scenario generator tool can produce several mobility models including our Shopping Mall mobility model. Distributions derived from the field study along with settings defining the environment, such as shopping mall plan and number of sellers in each shop, are submitted to the scenario generator to produce synthetic mobility traces from the Shopping Mall model.

We have evaluated the Shopping Mall mobility model by comparing its contact duration and inter-contact time distributions with those derived from real traces and the Random Way-Point mobility model. We reproduced and ran simulations of the shopping mall where we conducted the initial field trial. We observed that our Shopping Mall mobility model produces synthetic traces which approximate the real world traces. We also compared it with three other unstructured mobility models by evaluating two benchmark delay tolerant routing protocols, Epidemic and Prophet, against each model.

We concluded our work of thesis by analysing the possibility of delivering messages in such environments just forwarding them either to customers or sellers by means of semi-Epidemic routing protocols.

6.2 Critical Reflections

Much of the living beings' mobility within a specific scenario is to some extent goal-oriented and therefore potentially predictable. This is particularly true if there exists a "social" structure in which they live and which they are part of. For example, it has been shown that bees follow a goal-driven trajectory when flying out of their beehive looking for nectar and similarly for ants, wasps and insects in general. Almost any group of wild or domestic animals has its own defined social structures which give each animal a specific position and which influence internal and external relationships of the group. The social position of each individual can change with time and place. In this context, we are actually talking about communities; in biological terms, a community is a group of interacting individuals sharing a common environment.

This is also valid for human beings even though in this case the definition of community may be more complex [198]. Often, human beings belong to more than one community, and they may try to model the place in which they live so as to reflect their social structure. As an example I recall the traditional urban structure that places the church and the city council in front of the main square of the town. Human societies use space as a key and necessary resource in organizing themselves. Parts of the space can identify distinguishable groups, communities, or activities, and be associated with different rules of behaviour and conventions. However, since the advent of Internet, the concept of community no longer has geographical limitations, as people can virtually gather in an online community and share common interests regardless of physical location.

In my research project I have been focusing on possible applications for delay tolerant mobile ad-hoc networks in shopping mall environments. We chose such a scenario because it offers all of the elements required to build large-scale people-centric network applications. A shopping mall is a "microcosm" where a collection of shops all adjoin a pedestrian area or an exclusive pedestrian street. In many cases, shopping malls are tens of thousands of square meters in area and crowded much of the time. It represents a relatively democratic space with all people enjoying access, with participatory entertainment and opportunities for social mixing. Such characteristics are also typical of other scenarios which can be described by a plan, such as urban areas, megastructures, settlements, built complexes, museums, trade fairs, music festivals, stadiums, and so on. Besides, in such environments autonomic networks can sometimes be a better solution than traditional infrastructure-based networks because the latter can be more expensive, involve installation issues, incur customer cost, have particular policy restrictions, and may be less appropriate for people-centric networks where services are established on the fly.

By exploiting people's own computing devices, a delay tolerant mobile ad-hoc network may be built up in such a setting. In shopping mall environments shopkeepers might form a mobile ad-hoc network backbone and the starting point from which to build wider networks. The identification of such individuals of people could help greatly in forwarding data. Because of the devices' intrinsic mobility the topology of the network is time varying. Mobility compromises the communication between users, as forwarding paths may be unstable and receiver reachability may be highly variable. Understanding human mobility is important when designing routing protocols for applications for such mobile ad-hoc delay tolerant networks. Therefore, we decided to ground our work on the collection of real-world Bluetooth contact data from shop employees of a shopping mall. Because of practical reasons (see the experiment setup in Section 2.3) only sellers were involved in our experiment in a shopping mall. Therefore, our data set lacks contact traces from customers' personal devices to directly analyze inter-customers contacts. However, the observations we made in Chapter 2 along with those in Section 4.4 support the validity of the sellers' and customers' mobility models which implies that customers' movement is realistic and therefore that customer contact patterns should be realistic. In addition to that, our results are influenced by the granularity of the experiment. For short event lengths, the data is affected by the granularity of measurement, that is 120 seconds.

Furthermore, we cannot immediately distinguish between customers' and sellers' devices from our contact traces. We cannot assume that external contacts are between our smart phones and customers because the latter might be any other sellers' personal device. Therefore, we present a method based on contact duration, inter-contact time and frequency to distinguish two groups of people, visitors/customers and shopping mall related people, with different mobility patterns. Thus, this data allowed us to design and validate a novel mobility model which can be used by the research community to simulate such an environment.

Many research groups have studied different real mobility traces and real contact patterns to gain insight about the real mobile user behavior and to design realistic mobility models and more efficient routing protocols [181, 31, 193, 199]. One of the biggest issue with most of the synthetic models is that they are not capturing heterogeneous behaviour of nodes. Instead, our Shopping Mall mobility model is heterogeneous in both time and space, and captures several different mobility characteristics at a lower level of abstraction than many other previous models.

Ekman et al. [42] presented their Working Day mobility model which tries to capture several mobility characteristics at a lower level than many other models. Similar work was conducted by Minder et al. [43] in office environments. The mobility model presented in this thesis is part of this effort. We have decided to narrow down the playground scenario to structure environments, with particular regard to shopping malls, and to focus on compelling applications in such environments. For this reason, we have designed a novel mobility model based on real traces [47, 48]. The approach of our Shopping Mall mobility model is similar to the mobility models presented by Ekman et al. [42] and Minder et al. [43]. All of them use parameterised submodels discribing distinct periodic activities (movement model elements) at a given time. However, the two previous models generate homogeneous movement, that is every node follows the same instructions, while our model considers submodels for two distinct groups of people, customers and sellers, with different mobility patterns taking place at the same time. Besides, they used some distribution functions that assign time to all of the activities. We used the same approach to design a temporal structure which dictates how nodes move with in the shopping mall. In addition, our model also considers the distributions for the customers' inter-arrival time and their staying in the mall which makes the number of nodes in the simulation area varying with time. Furthermore, our mobility model and those proposed by Ekman et al. [42] and Minder et al. [43] are some of the models reproducing indoor movement.

In this thesis we have also shown that people's motion can be clustered based on several factors which are strongly related to the environment in which they are. We could have clustered people by distinguishing between different classes of individuals, for example between males and females. However, we decided to keep mobility pattern distinctions as simple as possible and chose to differentiate between two groups, customers and sellers, which in turn, have different mobility patterns. Therefore, we have characterized contact opportunity in shopping mall environments by analysing the mobility of people distinguishing between customers and sellers. Different patterns of mobility may give rise to different opportunity for communication, and different protocols may be more effective in particular situations. Therefore, although the distinction of classes of mobility in practical situations within shopping malls is somewhat obvious, we have presented evidence and some quantification of the ways in which they differ. These results are quite different from previous studies [1, 2, 29, 30, 31, 32, 33, 34, 80].

At this stage we have not analysed our data set in terms of community groups' mobility and mobility directions. In our current mobility model, customers wander individually within the shopping mall. The existence of groups or clusters of customers might be significant when designing more specific routing algorithms and application services in such environments. Besides, we assume that all of the shops have the same attraction level equal to 1, both for customers and sellers. With these settings, customers can go forwards and backwards within the shopping mall at random. This behaviour is not realistic, it does not appear suitable for large scale environments, but may be acceptable for small scale environments such as our shopping mall. In the future we would like to improve our mobility model by considering group relationships and people's directions in such an environment.

As shown in Chapter 4 we evaluate our mobility model by performing a number of tests and comparing the resulting mobility patterns, in terms of inter-contact times and contact durations, with the real-world contact traces collected in "our" shopping mall. Usually, inter-contact and contact time distributions are used in comparisons [119]. The description of these measurement exercises are presented in [1]. In that paper, the authors also compare their results with other publicly available data sets provided by McNett and Voelker from University of California at San Diego [55] and by Henderson et al. from Dartmouth College [33] showing evident similarities between the patterns movements collected by the three different groups. In the same way, Musolesi and Mascolo from University College London validate their mobility model founded on social network theory by comparing their results with another available data set of real traces provided by Intel Research Laboratory in Cambridge[1]. Mei et al. [45, 46] also compared their simulation results with three available data sets of real traces from the Computer Laboratory at the University of Cambridge and a conference at Infocom 2005[2] to validate their mobility model based on a simple intuition of human mobility. For this reason, we decided to compare the traces obtained by using our mobility model only with the contact traces from our data set. However, we are also aware that intrinsic characteristics of dynamic wireless networks cannot be totally captured by taking into account only the inter-contact time and contact duration distributions. Fleury et al. [200] introduced and presented some coupled arguments from data mining, random processes and graph theory in order to extract knowledge on dynamic networks. Nonetheless, we still think that the comparisons that we presented are useful and show that our Shopping Mall mobility model is a much closer approximation to real traces than traditional random mobility models. Anyway, in future work we would like to look at such other characteristics and consider these to improve our mobility model.

Finally, we showed the impact of different mobility models on the performance of two benchmark routing protocols, Epidemic and Prophet, in the mall-based scenarios. Therefore, we compared the simulation results of four distinct mobility models having nodes' movements with different degree of freedom. These are, in order of decreasing degree of freedom, the Random Walk, the Random Way-Point with inter-arrival time, the Random Walk with with inter-arrival time and the Shopping Mall mobility model.

Furthermore, to understand better the role of groups of message carriers expressing different mobility patterns, we performed simulations of a derivative of the Epidemic protocol which distinguishes between customers and sellers, and entrusts messages through either one or the other. Such semi-Epidemic is a flooding-based protocol which does not use any knowledge of the system but distinguishing between customers and sellers to forward mes-

[1]Some features of the Intel Research Laboratory data set are shown in the Tables 2.1 and 2.2.

[2]Some features of the Computer Laboratory and Infocom data sets are shown in the Tables 2.1 and 2.2

sages. In such way we have shown that under some circumstances it might be preferable forwarding messages to sellers rather than customers. Such information might be taken into account to design routing protocols for delay-tolerant mobile ah-hoc networks in structured scenarios.

In previous study, Grossglauser and Tse [72] argued that "Mobility Increases the Capacity of Ad Hoc Wireless Networks", considering issues related to Physical and MAC layers such as multipath fading, path loss via distance attenuation, shadowing by obstacles, and interference from other users. They simulated a two-hops routing protocol with an ad-hoc network consisting of n mobile nodes with infinite buffer to store relayed packets, all lying in the disk of unit area of radius $1/\sqrt{\pi}$ which trajectories are independent and identically distributed. Their results suggest that delay-tolerant applications can take advantage of node mobility to significantly increase the throughput capacity of such networks. It would be interesting to study how much throughput can be achieved also considering Physical and MAC layers when nodes have less random mobility patterns. Maybe, in structured environments where nodes have mostly goal-oriented mobility what Grossglauser and Tse argued is not always true. Our structured mobility model can be used to perform such a study.

6.3 Contributions

Measurements in public places and their statistical analysis help in characterizing realistic mobility models. My first contribution offered to the research community is a valuable dataset of real-world Bluetooth contact traces collected in a shopping mall. For that, I programmed twenty-five smart phones, which run SymbianOS operating system, to log other Bluetooth devices within communication range. We have presented real-world measurement results from the mobility of people in shopping mall environments.

Second, we performed extensive analysis of the collected contact traces. We analysed the contact time and inter-contact time distributions and confirmed as expected that the inter-contact time for each pair follows a heavy-tail distribution. These results are quite different from previous studies in workplace [30], university campus [1, 31, 32, 33, 34]and conference scenarios [2], where power law coefficients approximate the inter-contact time distributions for longer periods of time. We have identified groups of people who exhibit higher power law coefficients but only for short time periods. This is significant in that using multiple intermediate relays may be sufficient for stateless forwarding algorithms to converge [1]. The observed distributions suggest that forwarding to neighboring sellers and shop assistants might increase the likelihood of timely contact. We believe that shopkeepers could form a mobile ad-hoc network backbone and the starting point from which to build wider networks in shopping mall environments. The identification of such groups of people could help greatly in forwarding data. We observed that forwarding algorithms do not appear to need to take into account broad temporal patterns in this environment.

Third, we derived several cumulative distribution functions describing the mobility behaviour of customers and sellers. Such distributions are important parameters for our Shopping Mall mobility model and may be employed as a starting point to model different kinds of shopping mall-like environments. Although the identification of different classes of mobility within the shopping mall is somewhat obvious, we have presented evidence of this and some quantifications of their characteristics. For that, we developed a technique based on contact duration, inter-contact time and number of contacts to identify two groups of people, customers/visitors and sellers/shopping mall related people, performing different mobility patterns. Such technique could also be employed to identify individuals in well-structured scenarios.

Fourth, we propose a new mobility model for shopping mall environments based on real traces and the empirical understanding of human mobility. We also developed a mobility scenario generation tool, a Java application which generates mobility traces for this and also some standard mobility models. Our scenario generator allows new models to be easily plugged-in (see Section 3.4.2). Our shopping mall mobility model has been validated through large-scale simulations and comparisons with real traces and a Random WayPoint-like mobility model. Our scenario generator and Shopping Mall mobility model are available upon request to the research community.

Fifth, as a proof of concept, we tested and evaluated Epidemic and Prophet, two well-known routing protocols employed in Delay Tolerant Networks, with our Shopping Mall and three other mobility models. We showed that the choice of mobility model affects the performance of both routing protocols and thus that traditional mobility models should not be used to simulate "structured" scenarios. By comparing the performance of such different routing protocols on different mobility models we give evidence that the choice of mobility model can be a critical consideration in designing and evaluating of routing protocols for delay-tolerant mobile ah-hoc networks.

Finally, we designed a derivative of the Epidemic protocol which distinguishes between customers and sellers, and entrusts messages through either one or the other. This allows us to understand better the role of groups of message carriers expressing different mobility patterns. We have shown that under some circumstances it might be preferable forwarding messages to some carriers rather than others. Such information can help in the design of routing protocols for delay-tolerant mobile ah-hoc networks in structured environments.

6.4 Future Work

We believe that different environments are characterized by different patterns of mobility and should be supported by suitable embedded routing protocols. Therefore collecting data reflecting human mobility is important when designing routing protocols for such mobile ad-hoc delay tolerant networks.

In this thesis we have started with a particular shopping mall. However, we envision different scenarios each characterized by their mobility patterns and embedded routing algorithm, all of which may be part of a large system which could interconnect each environment. In the future we would like to collect contact data in a number of other "structured" environments such as trade fairs, music festivals, automobile race tracks, stadiums, museums, to analyse their mobility patterns and identify possible key characteristics to take into account when designing routing protocols and representative mobility models for more diverse settings.

We would also like to analyse larger scale scenarios and therefore we would need to consider a more complex modelling of movement within the mall. In our scenario, we assumed that all of the shops had the same attraction level equal to 1, both for customers and sellers. With these settings, customers can go forwards and backwards within the shopping mall at random. This behaviour may be acceptable for small scale environments such as our shopping mall but it does not appear suitable for large scale environments.

Moreover, we would like to improve our mobility model by considering group relationships. In our current model, customers wander individually within the shopping mall. The existence of groups or clusters of customers might be significant when designing more specific routing algorithms and application services in such environments.

We would like to develop a simulation system where the simulated area is structured and composed of different interconnected subscenarios. Such a configuration of the space will change it from continuous into a connected set of discrete place units which allows the identification and application of different labels to its individual parts. These parts of the space can identify distinguishable groups, communities, or activities, and be associated with different rules of behaviour and conventions. An existent social structure can be mapped onto the configured space. The demarcation of boundaries allows particular relationships of access or visibility to emerge among the component spaces, and this in turn generates probabilistic patterns of movement and encounter within the population. This representation of the whole scenario allows the user to understand better different types of environments by looking at the settings on a different scale.

Finally, we would also like to design and test forwarding algorithms for structured environments that exploit the intrinsic characteristics of such scenarios. We envisage a broad range of structured scenarios, from urban areas to megastructures, from shopping malls to trade fairs, and from stadiums to museums, where any kind of network device is able to communicate through autonomic interconnected networks.

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Appendix

Appendix A

Previous Experiments

A.1 Inter-contact time distributions for the Cambridge data sets

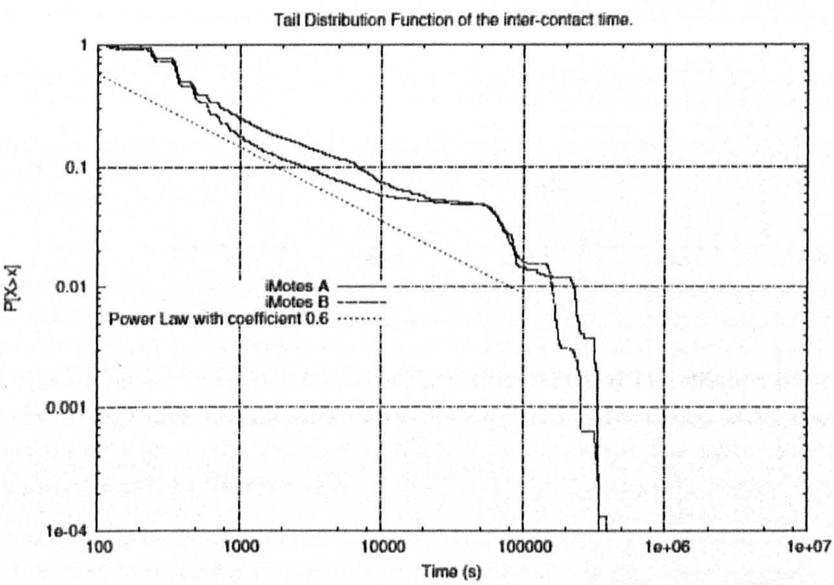


Figure A.1: Inter-contact time distributions for the iMote A and iMote B data sets. Experiment iMote A included nine researchers and interns working at Intel Research Cambridge, while iMote B involved twelve doctoral students and faculty comprising a research group at the University of Cambridge Computer Lab (Source [1]).

A.2 Inter-contact time distributions for the UCSD and Dartmouth data sets

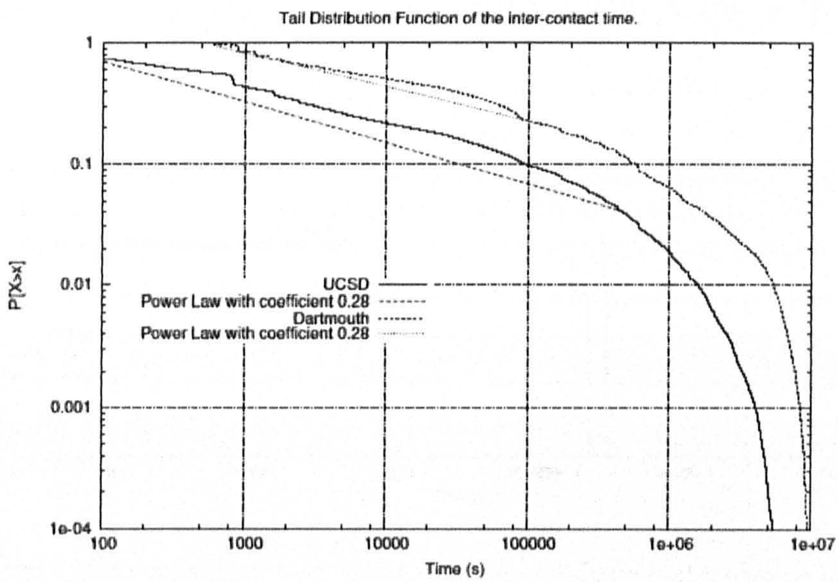


Figure A.2: Inter-contact time distributions for the UCSD and Dartmouth data sets. Both data sets from UCSD and Dartmouth make use of WiFi networking, with the former including client-based logs of the visibility of access points, while the latter includes SNMP logs from the access points (Source [1]).

A.3 Distribution of inter-contact times between iMotes

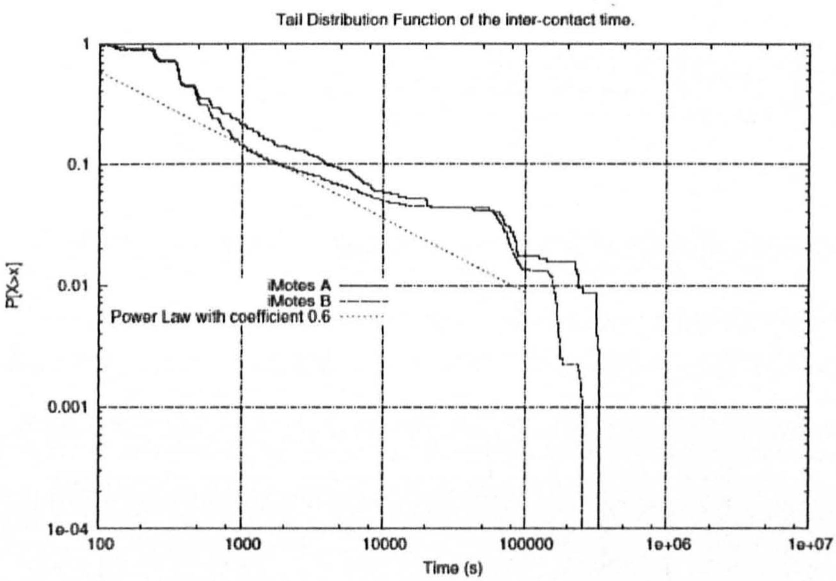


Figure A.3: Distribution of inter-contact times between iMotes. Experiment iMote A included nine researchers and interns working at Intel Research Cambridge, while iMote B involved twelve doctoral students and faculty comprising a research group at the University of Cambridge Computer Lab (Source [1]).

A.4 Distribution of inter-contact times between iMotes and other Bluetooth devices

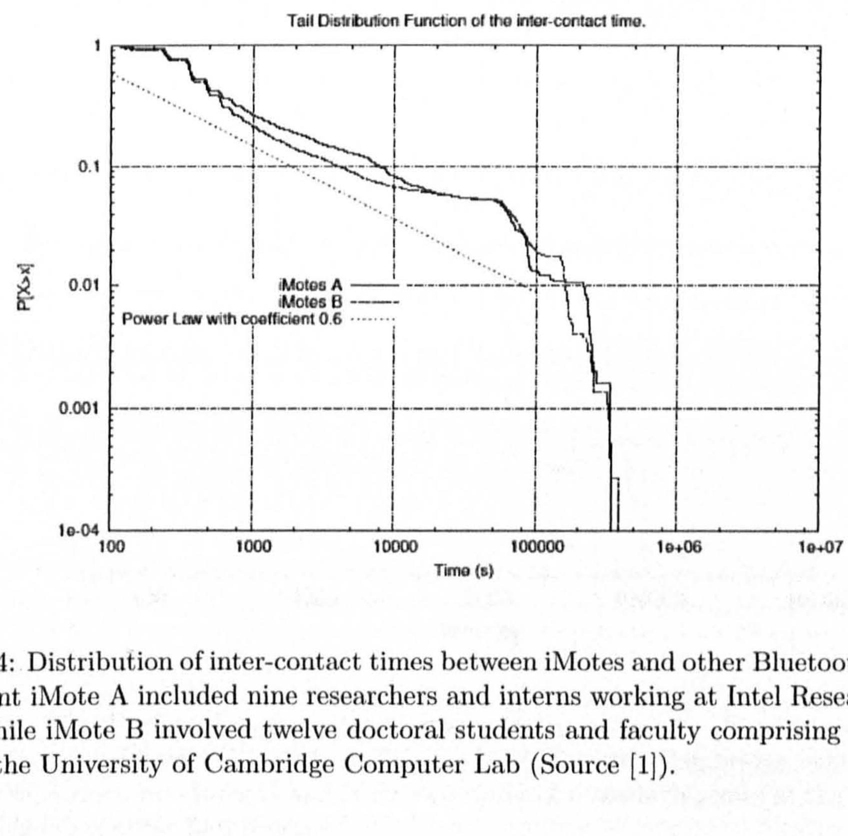


Figure A.4: Distribution of inter-contact times between iMotes and other Bluetooth devices. Experiment iMote A included nine researchers and interns working at Intel Research Cambridge, while iMote B involved twelve doctoral students and faculty comprising a research group at the University of Cambridge Computer Lab (Source [1]).

A.5 Distribution of contact duration for iMotes data sets

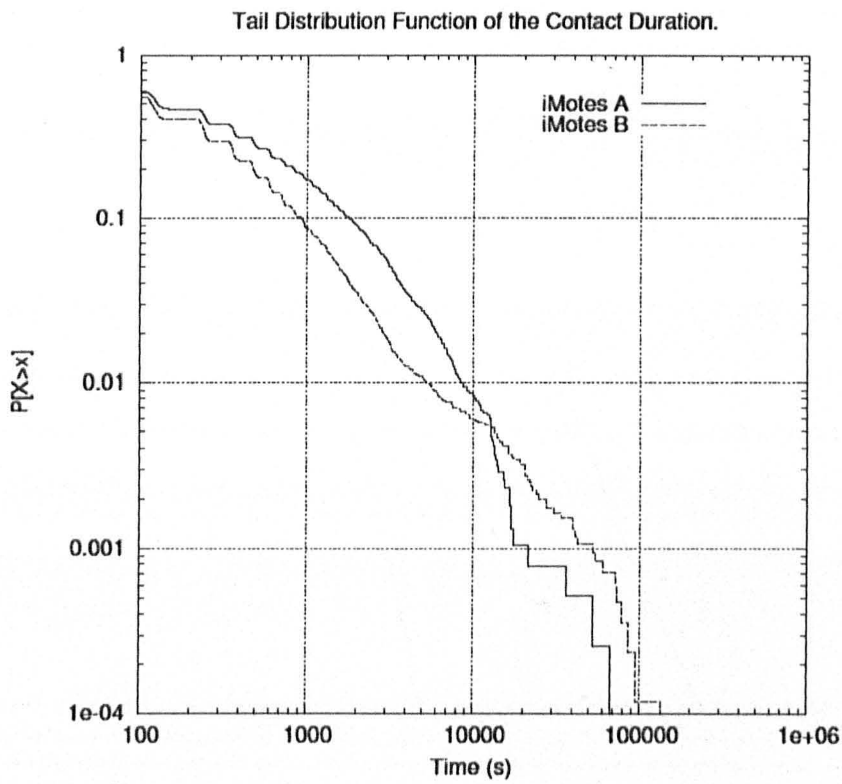


Figure A.5: Distribution of contact duration for iMotes data sets. Experiment iMote A included nine researchers and interns working at Intel Research Cambridge, while iMote B involved twelve doctoral students and faculty comprising a research group at the University of Cambridge Computer Lab (Source [1]).

A.6 Distribution of contact duration for WiFi data sets

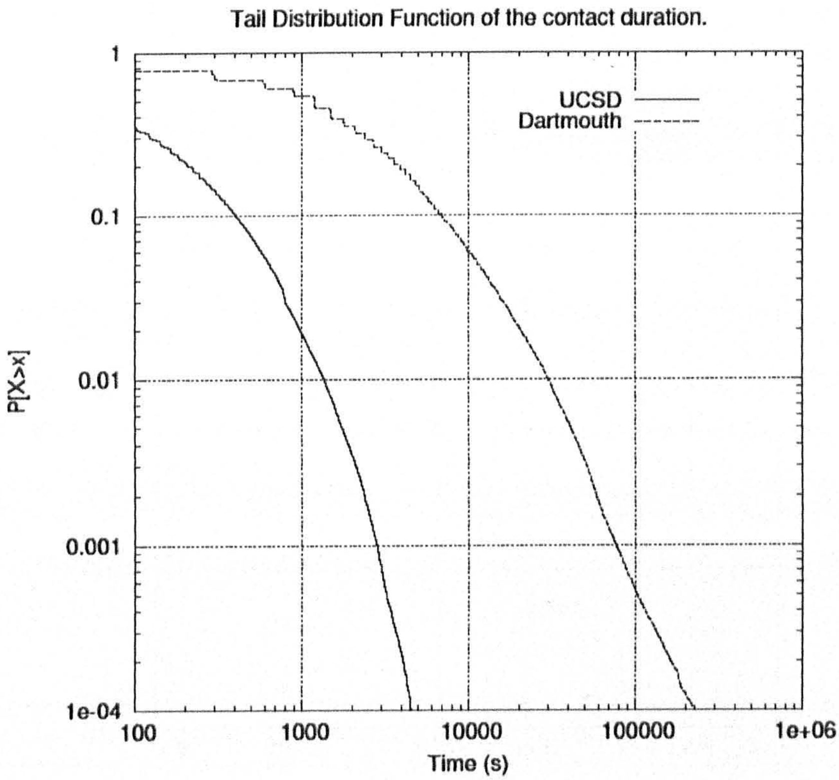


Figure A.6: Distribution of contact duration for WiFi data sets from UCSD and Dartmouth (Source [1]).

A.7 Inter-contact time distributions in Conference Environments

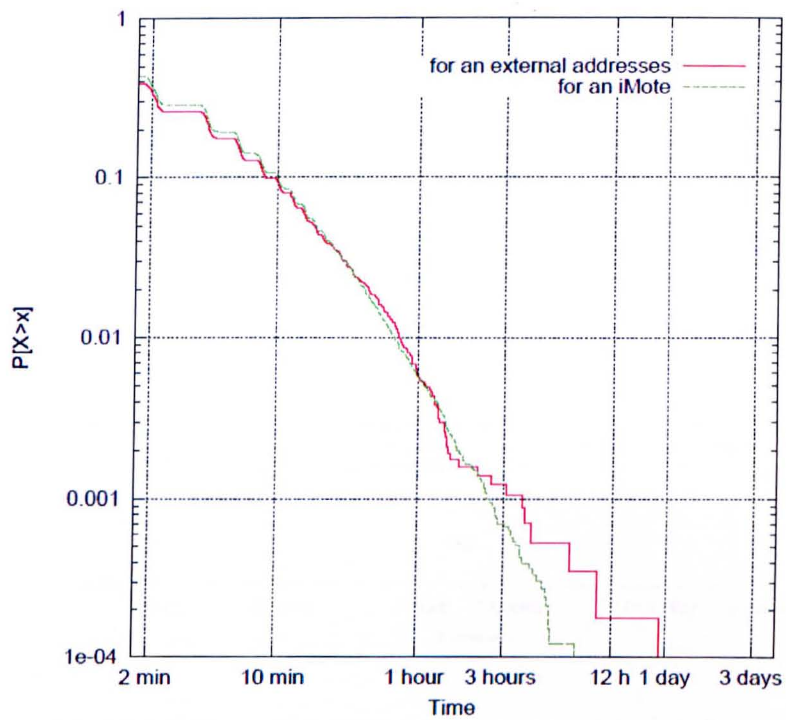


Figure A.7: Distributions of inter-contact times for pairs of nodes (Source [2]).

A.8 Contact time distributions in Conference Environments

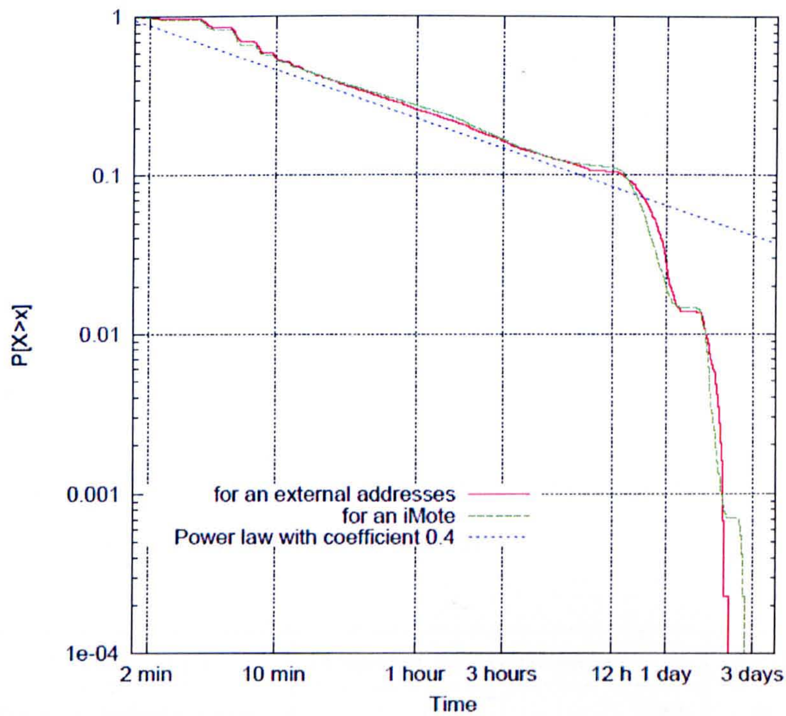


Figure A.8: Distributions of contact times for pairs of nodes (Source [2]).

Appendix B

Empirical Coefficient Values for Indoor Propagation

B.1

Empirical measurements of coefficients γ and $\sigma[dB]$ in dB have shown the following values for a number of indoor wave propagation cases [133].

Building Type	Frequency of Transmission	γ	$\sigma[dB]$
Vacuum, infinite space		2.0	0
Retail store	914 MHz	2.2	8.7
Grocery store	914 MHz	1.8	5.2
Office with hard partition	1.5 GHz	3.0	7
Office with soft partition	900 MHz	2.4	9.6
Office with soft partition	1.9 GHz	2.6	14.1
Textile or chemical	1.3 GHz	2.0	3.0
Textile or chemical	4 GHz	2.1	7.0, 9.7
Metalworking	1.3 GHz	1.6	5.8
Metalworking	1.3 GHz	3.3	6.8

Appendix C

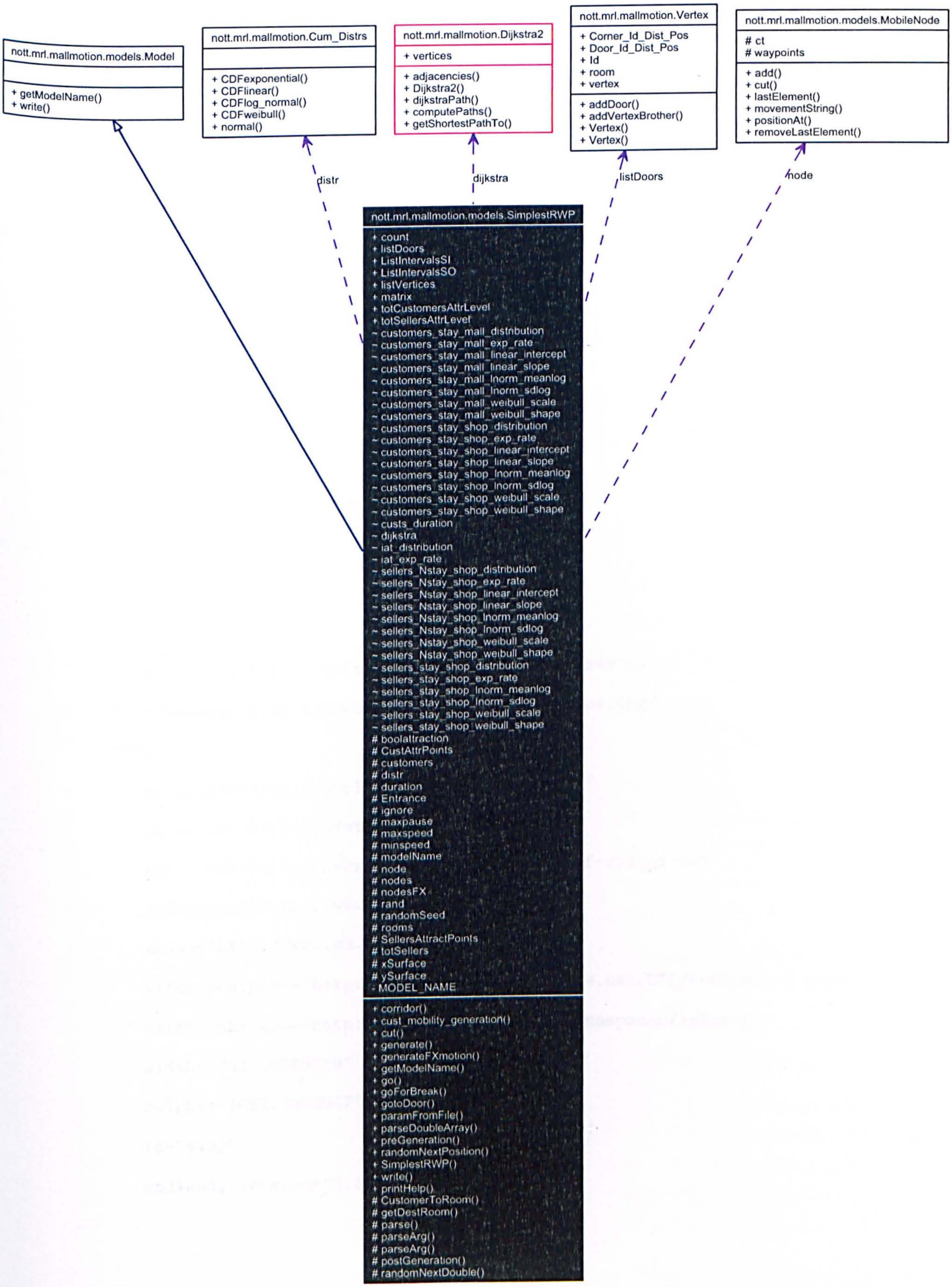
Details of the Implementation

Our Java software tool produces traces mainly for the Omnet++ simulator [53], one of the most popular discrete event network simulation framework in the mobile ad hoc network research community. The software has been tested with Java 1.5.0_11 and 1.6.0_15. This mobility model generation tool is available to other research groups upon request. In this section we describe the main components and features of the software developed.

- Our mobility model generator is composed of a class `MM` which is the starting point of the entire structure. MM looks in its list of implemented models and gets a class object which represents a mobility model. In this way, further models can be easily plugged-in. A public member function go determines the class to run which is the model specified on the command line and passes the parameters to the model itself. This method uses reflection to look in its list of implemented models. Reflection is useful when it is not convenient or possible to hard-code a given method call or field access into the code. A given class or method can be configured in a file or otherwise determined while the program is running. The call graphs for MM are in Appendix D.1.

- I have implemented three classes which can reproduce several mobility models: `MallMotion`, `RandomWayPoint` and `SimplestRWP` (see UML diagram in Appendix D.2). In Section 3.4.3 we describe the five mobility models that can be generated with this tool.

- This software tool needs refactoring in order to improve code readability and reduce complexity of maintainability of the source code as well as to structure better the internal architecture so that to facilitate extensibility. At moment it is organized in 5 packages:
  - `mallmotion.run`, where the class `MM` is located;
  - `mallmotion.models` contains the implementations of all the mobility models are placed;
  - `mallmotion` contains several classes which define nodes, the Dijkstra's algorithm and the structure of the playground;
  - `math`, an external Java library which includes mathematics and statistics components addressing the most common problems not available in the Java programming language [102].
  - `SSJ`, an external Java library for stochastic simulation developed in the Département d'Informatique et de Recherche Opérationnelle (DIRO), at the Université de Montréal [101].



nott.mrl.mallmotion.models.Model
+ getModelName()
+ write()
nott.mrl.mallmotion.Cum_Distrs
+ CDFexponential()
+ CDFlinear()
+ CDFlog_normal()
+ CDFweibull()
+ normal()
nott.mrl.mallmotion.Dijkstra2
+ vertices
+ adjacencies()
+ Dijkstra2()
+ dijkstraPath()
+ computePaths()
+ getShortestPathTo()
nott.mrl.mallmotion.Vertex
+ Corner_Id_Dist_Pos
+ Door_Id_Dist_Pos
+ Id
+ room
+ vertex
+ addDoor()
+ addVertexBrother()
+ Vertex()
+ Vertex()
nott.mrl.mallmotion.models.MobileNode
ct
waypoints
+ add()
+ cut()
+ lastElement()
+ movementString()
+ positionAt()
+ removeLastElement()
distr
dijkstra
listDoors
node
nott.mrl.mallmotion.models.SimplestRWP
+ count
+ listDoors
+ ListIntervalsSI
+ ListIntervalsSO
+ listVertices
+ matrix
+ totCustomersAttrLevel
+ totSellersAttrLevel
~ customers_stay_mall_distribution
~ customers_stay_mall_exp_rate
~ customers_stay_mall_linear_intercept
~ customers_stay_mall_linear_slope
~ customers_stay_mall_lnorm_meanlog
~ customers_stay_mall_lnorm_sdlog
~ customers_stay_mall_weibull_scale
~ customers_stay_mall_weibull_shape
~ customers_stay_shop_distribution
~ customers_stay_shop_exp_rate
~ customers_stay_shop_linear_intercept
~ customers_stay_shop_linear_slope
~ customers_stay_shop_lnorm_meanlog
~ customers_stay_shop_lnorm_sdlog
~ customers_stay_shop_weibull_scale
~ customers_stay_shop_weibull_shape
~ custs_duration
~ dijkstra
~ iat_distribution
~ iat_exp_rate
~ sellers_Nstay_shop_distribution
~ sellers_Nstay_shop_exp_rate
~ sellers_Nstay_shop_linear_intercept
~ sellers_Nstay_shop_linear_slope
~ sellers_Nstay_shop_lnorm_meanlog
~ sellers_Nstay_shop_lnorm_sdlog
~ sellers_Nstay_shop_weibull_scale
~ sellers_Nstay_shop_weibull_shape
~ sellers_stay_shop_distribution
~ sellers_stay_shop_exp_rate
~ sellers_stay_shop_lnorm_meanlog
~ sellers_stay_shop_lnorm_sdlog
~ sellers_stay_shop_weibull_scale
~ sellers_stay_shop_weibull_shape
# boolattraction
# CustAttrPoints
# customers
# distr
# duration
# Entrance
# ignore
# maxpause
# maxspeed
# minspeed
# modelName
# node
# nodes
# nodesFX
# rand
# randomSeed
# rooms
# SellersAttractPoints
# totSellers
# xSurface
# ySurface
- MODEL_NAME
+ corridor()
+ cust_mobility_generation()
+ cut()
+ generate()
+ generateFXmotion()
+ getModelName()
+ go()
+ goForBreak()
+ gotoDoor()
+ paramFromFile()
+ parseDoubleArray()
+ preGeneration()
+ randomNextPosition()
+ SimplestRWP()
+ write()
+ printHelp()
# CustomerToRoom()
# getDestRoom()
# parse()
# parseArg()
# parseArg()
# postGeneration()
# randomNextDouble()

Appendix E

SVG Textual Mode

E.1 Shopping Mall Plan

```
<?xml version="1.0" encoding="UTF-8" standalone="no"?>
<!-- Created with Inkscape (http://www.inkscape.org/) -->
<svg
   xmlns:dc="http://purl.org/dc/elements/1.1/"
   xmlns:cc="http://creativecommons.org/ns#"
   xmlns:rdf="http://www.w3.org/1999/02/22-rdf-syntax-ns#"
   xmlns:svg="http://www.w3.org/2000/svg"
   xmlns="http://www.w3.org/2000/svg"
   xmlns:sodipodi="http://sodipodi.sourceforge.net/DTD/sodipodi-0.dtd"
   xmlns:inkscape="http://www.inkscape.org/namespaces/inkscape"
   width="744.09448819"
   height="1052.3622047"
   id="svg2"
   sodipodi:version="0.32"
```

```
   inkscape:version="0.46"
   sodipodi:docname="drawing5c061109-4-2a.svg"
   inkscape:output_extension="org.inkscape.output.svg.inkscape">
  <defs
     id="defs4">
    <inkscape:perspective
       sodipodi:type="inkscape:persp3d"
       inkscape:vp_x="0 : 526.18109 : 1"
       inkscape:vp_y="0 : 1000 : 0"
       inkscape:vp_z="744.09448 : 526.18109 : 1"
       inkscape:persp3d-origin="372.04724 : 350.78739 : 1"
       id="perspective10" />
  &lt;/defs&gt;
  <sodipodi:namedview
     id="base"
     pagecolor="#ffffff"
     bordercolor="#666666"
     borderopacity="1.0"
     gridtolerance="10000"
     guidetolerance="10"
     objecttolerance="10"
     inkscape:pageopacity="0.0"
     inkscape:pageshadow="2"
     inkscape:zoom="2.8284271"
     inkscape:cx="188.94581"
     inkscape:cy="931.36965"
     inkscape:document-units="px"
     inkscape:current-layer="layer1"
```

```
    showgrid="false"
    inkscape:window-width="1154"
    inkscape:window-height="884"
    inkscape:window-x="120"
    inkscape:window-y="80"
    showguides="true">
   <inkscape:grid
      type="xygrid"
      id="grid3275" />
</sodipodi:namedview>
<metadata
    id="metadata7">
   <rdf:RDF>
     <cc:Work
        rdf:about="">
       <dc:format>image/svg+xml</dc:format>
       <dc:type
          rdf:resource="http://purl.org/dc/dcmitype/StillImage" />
     </cc:Work>
   </rdf:RDF>
</metadata>
<g
   inkscape:label="Layer 1"
   inkscape:groupmode="layer"
   id="layer1">
  <path
     style="fill:none;fill-rule:evenodd;stroke:#000000;stroke-width:
     0.92304605;stroke-linecap:butt;stroke-linejoin:miter;stroke-miterlimit:
```

```
       4;stroke-dasharray:none;stroke-opacity:1"
       d="M 42.664105,58.879147 L 35.293687,58.879147 L 35.293687,0.85724238
       L 59.217338,0.85724238 L 59.217338,58.879147 L 49.672039,58.879147"
       id="path2381"
       sodipodi:nodetypes="cccccc" />
...
    <text
       sodipodi:linespacing="100%"
       id="text2775"
       y="58.551208"
       x="33.811153"
       style="font-size:3.69739366px;font-style:normal;font-variant:normal;
       font-weight:normal;font-stretch:normal;text-align:start;line-height:
       100%;writing-mode:lr-tb;text-anchor:start;fill:#000000;fill-opacity:
       1;stroke:none;stroke-width:1px;stroke-linecap:butt;stroke-linejoin:
       miter;stroke-opacity:1;font-family:Arial;-inkscape-font-specification:
       Arial"
       xml:space="preserve"
       transform="scale(0.9160027,1.0916999)"><tspan
         y="58.551208"
         x="33.811153"
         id="tspan2777"
         sodipodi:role="line">v:2</tspan></text>
...
  </g>
</svg>
```

Appendix F

omnetpp.ini

F.1

```
[General]
cmdenv-config-name = perftest
cmdenv-express-mode = true
cmdenv-performance-display = true
cmdenv-status-frequency = 2s
fname-append-host = true
ned-path = ../../base;../../modules;../../examples;
network = sim

#output-vector-file = "${resultdir}/${configname}-${runnumber}.vec"
#output-scalar-file = "${resultdir}/${configname}-${runnumber}.sca"
result-dir = results/mall
sim-time-limit = 43200s
```

```
##############################
#  Simulation parameters  #
##############################
record-eventlog = true
tkenv-default-config =
**.node[0-50].module-eventlog-recording = true
**.scalar-recording = true
**.vector-record-eventnumbers = true
**.vector-recording = true

sim.**.coreDebug = false

sim.playgroundSizeX = 800m
sim.playgroundSizeY = 500m
sim.playgroundSizeZ = 0m
sim.numNodes =  179

##############################
#  WorldUtility parameters  #
##############################
sim.world.useTorus = false
sim.world.use2D = true

#########################
#  channel parameters  #
#########################
sim.connectionManager.debug = false
sim.connectionManager.radioRange = 85
```

```
sim.connectionManager.sendDirect = false
# max transmission power [mW]
sim.connectionManager.pMax = 2.5mW
# signal attenuation threshold [dBm]
sim.connectionManager.sat = -65dBm
# path loss coefficient alpha
sim.connectionManager.alpha = 2.2
# carrier frequency in hertz
sim.connectionManager.carrierFrequency = 2.412e+9Hz



####################################
#  Parameters for the Mac Layer  #
####################################

# debug switch
sim.node[*].nic.mac.headerLength = 272
sim.node[*].nic.mac.queueLength = 14
sim.node[*].nic.mac.bitrate = 3E+6bps #2E+6bps# in bits/second   #Bluetooth
sim.node[*].nic.mac.defaultChannel = 0
sim.node[*].nic.mac.autoBitrate = false

### values if no fading is modelled, gives at most 1% packet error rate
sim.node[*].nic.mac.snr2Mbit = 1.46dB  # [dB]
sim.node[*].nic.mac.snr5Mbit = 2.6dB  # [dB]
sim.node[*].nic.mac.snr11Mbit = 5.68dB  # [dB]
```

```
sim.node[*].nic.mac.rtsCtsThreshold = 400
sim.node[*].nic.mac.neighborhoodCacheSize = 300   #keeps information on neighbors
sim.node[*].nic.mac.neighborhoodCacheMaxAge = 100s # [s] Mac80211: double
                                            # neighborhoodCacheMaxAge @unit(s)
                                            #"consider information in cache outdate
                                            #if older than (in seconds)"

#how long is a slot? [s]
sim.node[*].nic.mac.slotDuration = 0.04s
#maximum time between a packet and its ack [s]
sim.node[*].nic.mac.difs = 0.0005s
#maximum number of transmission attempts
sim.node[*].nic.mac.maxTxAttempts = 1000

#contention window
sim.node[*].nic.mac.contentionWindow = 20
# transmission power [mW]
sim.node[*].nic.mac.txPower = 100mW  # [mW]

############################
#  Parameters for the Phy  #
############################

# debug switch
**.playgroundSizeZ = 0
**.net.stats = false
**.mac.txPower = 110.11mW  # [mW]
```

```
**.phy.usePropagationDelay = false
**.phy.thermalNoise = -110dBm  # [dBm]
**.phy.analogueModels = xmldoc("config.xml")
**.phy.decider = xmldoc("config.xml")

**.phy.sensitivity = -61dBm  # [dBm]
**.phy.maxTXPower = 110.11mW
**.phy.timeRXToTX = 0s
**.phy.timeRXToSleep = 0s
**.phy.timeTXToRX = 0s
**.phy.timeTXToSleep = 0s
**.phy.timeSleepToRX = 0s
**.phy.timeSleepToTX = 0s
**.phy.initialRadioState = 0
**.mobility.z = 0
sim.node[*].nic.phy.useThermalNoise = true

#############################
#   NETW layer parameters   #
#############################

sim.node[*].net.isSwitch = false
sim.node[*].net.maxTtl = 3
sim.node[*].net.boredTime = 0.5

###########################
#   Mobility parameters   #
###########################
```

```
sim.node[*].mobility.x = -1
sim.node[*].mobility.y = -1
sim.node[*].mobility.z = 0

sim.node[*].applType = "BurstApplLayer"
sim.node[*].mobType = "BonnMotionMobility"
sim.node[*].netwType = "BaseNetwLayer"
sim.node[*].appl.debug = false
sim.node[*].appl.headerLength = 512bit
sim.node[*].net.debug = false
sim.node[*].net.stats = false
sim.node[*].net.headerLength = 32bit
sim.node[*].appl.burstSize = 1
sim.node[*].mobility.traceFile = "scenario.movements"
sim.node[*].mobility.nodeId = -1
sim.node[*].mobility.debug = false
sim.node[*].mobility.speed = 0mps
sim.node[*].mobility.updateInterval = 0.5s
```

Appendix G

config.xml

G.1

```
<?xml version="1.0" encoding="UTF-8"?>
< root>
    < AnalogueModels>
        < AnalogueModel type="SimplePathlossModel">
        < parameter name="alpha" type="double" value="2.2"/>
        < parameter name="carrierFrequency" type="double" value="2.412e+9"/>
      </AnalogueModel>
    </AnalogueModels>
    < Decider type="Decider80211">
        <!-- SNR threshold [NOT dB] -->
        < parameter name="threshold" type="double" value="10"/>
        < !-- The center frequency on whcih the phy listens-->
        < parameter name="centerFrequency" type="double" value="2.412e9"/>
    </Decider>
</root>
```

Appendix H

NED files

H.1 Network.ned

```
package org.mixim.examples.mallnet80211;

import org.mixim.base.connectionManager.ConnectionManager;
import org.mixim.modules.connectionManager.UnitDisk;
import org.mixim.base.modules.BaseWorldUtility;

module BaseNetwork
{
    parameters:
        double playgroundSizeX @unit(m); // x size of the area the nodes are in
                                         // (in meters)
        double playgroundSizeY @unit(m); // y size of the area the nodes are in
                                         // (in meters)
        double playgroundSizeZ @unit(m); // z size of the area the nodes are in
```

```
                                   // (in meters)
    double numNodes; // total number of hosts in the network

    @display("bgb=122,160,white;bgp=0,0;bgs=2,m;bgi=maps/mall240x160");

  submodules:
    connectionManager: ConnectionManager {
        parameters:
            @display("p=381,302;b=42,42,rect,green;i=abstract/multicast");
    }
    world: BaseWorldUtility {
        parameters:
            playgroundSizeX = playgroundSizeX;
            playgroundSizeY = playgroundSizeY;
            playgroundSizeZ = playgroundSizeZ;
            @display("p=27,302;i=misc/globe");
    }
    node[numNodes]: BaseNode {
        parameters:
            @display("p=176,78;i=device/pocketpc_mine;is=vs");
    }
  connections allowunconnected:
}

network sim extends BaseNetwork
{
  parameters:
}
```

H.2 Node.ned

```
    package org.mixim.examples.mallnet80211;

import org.mixim.base.modules.*;
import org.mixim.modules.nic.Nic80211;

module BaseNode
{
    parameters:
        string applType; //type of the application layer
        string netwType; //type of the network layer
        string mobType; //type of the mobility module
        @display("bgb=,,white,,");
    gates:
        input radioIn; // gate for sendDirect
    submodules:
        utility: BaseUtility {
            parameters:
                @display("p=130,38,rect;b=24,24,,black,,");
        }
        arp: BaseArp {
            parameters:
                @display("p=130,84,rect;b=24,24,,blue,,");
        }
        mobility: < mobType> like IBaseMobility {
```

```
        parameters:
            @display("p=130,172;i=cogwheel2");
    }
    appl: < applType> like IBaseApplLayer {
        parameters:
            @display("p=60,50;i=app");
    }
    net: < netwType> like IBaseNetwLayer {
        parameters:
            @display("p=60,108;i=prot1");
    }
    nic: Nic80211 {
        parameters:
            @display("p=60,166;i=iface");
    }
connections:
nic.upperGateOut --> net.lowerGateIn;
nic.upperGateIn <-- net.lowerGateOut;
nic.upperControlOut --> { @display("ls=red;m=m,70,0,70,0"); } --> net.lowerControlIn;
nic.upperControlIn <-- { @display("ls=red;m=m,70,0,70,0"); } <-- net.lowerControlOut;

net.upperGateOut --> appl.lowerGateIn;
net.upperGateIn <-- appl.lowerGateOut;
net.upperControlOut --> { @display("ls=red;m=m,70,0,70,0"); } --> appl.lowerControlIn;
net.upperControlIn <-- { @display("ls=red;m=m,70,0,70,0"); } <-- appl.lowerControlOut;

radioIn --> nic.radioIn;
}
```

H.3 Nic80211.ned

```
package org.mixim.modules.nic;

import org.mixim.modules.mac.Mac80211;

import org.mixim.modules.phy.PhyLayer;

//
// This NIC implements an 802.11 network interface card.
//
// @see Mac80211, Decider80211
// @author Marc Loebbers, Karl Wessel (port for MiXiM)
//
module Nic80211
{
gates:
    input upperGateIn; // to upper layers
    output upperGateOut; // from upper layers
    output upperControlOut; // control information
    input upperControlIn; // control information
    input radioIn; // radioIn gate for sendDirect

submodules:
    mac: Mac80211 {
          @display("p=96,87;i=block/layer");
```

```
        }

    phy: PhyLayer {
            @display("p=106,157;i=block/process_s");
        }

connections:
mac.upperGateOut --> { @display("ls=black;m=m,25,50,25,0"); } --> upperGateOut;
mac.upperGateIn <-- { @display("ls=black;m=m,15,50,15,0"); } <-- upperGateIn;
mac.upperControlOut --> { @display("ls=red;m=m,75,50,75,0"); } --> upperControlOut;
mac.upperControlIn <-- { @display("ls=red;m=m,85,0,85,0"); } <-- upperControlIn;

phy.upperGateOut --> { @display("ls=black;m=m,25,50,25,0"); } --> mac.lowerGateIn;
phy.upperGateIn <-- { @display("ls=black;m=m,15,50,15,0"); } <-- mac.lowerGateOut;
phy.upperControlOut --> { @display("ls=red;m=m,75,50,75,0"); } --> mac.lowerControlIn;
phy.upperControlIn <-- { @display("ls=red;m=m,85,0,85,0"); } <-- mac.lowerControlOut;

radioIn --> phy.radioIn;
}
```

Appendix I

`omnetpp.ini` for Epidemic, Prophet and semi-Epidemic Routing Protocols

I.1

```
[General]

network = mobilityscenario
sim-time-limit=18000
ini-warnings = yes
num-rngs=25

[Parameters]
mobilityscenario.numberOfHosts=908
```

```
mobilityscenario.msgBufSize=100
mobilityscenario.maxHops=10
mobilityscenario.retransmissionInterval=134
mobilityscenario.dataCollector.numBinsDelayStat=40
mobilityscenario.dataCollector.maxRangeDelayStat=2400

[Cmdenv]
runs-to-execute=1
module-messages = no
verbose-simulation = no
express-mode=yes
performance-display= no

[Tkenv]
default-run=2
animation-speed=15.0
update-freq-fast=50
update-freq-express=500
animation-enabled=yes
```

Appendix J

NED File for Epidemic, Prophet and semi-Epidemic Routing Protocols

J.1

```
simple Host
    gates:
        in: controlInput, inputs[];
        out: outputs[];
endsimple


simple Engine
```

```
    gates:
        in: ingate;
        out: outgate;
endsimple


simple SimController
    gates:
        in: ingate;
        out: outgate;
endsimple


simple DataCollector
    parameters:
        numBinsDelayStat:const,
        maxRangeDelayStat:const;
    gates:
        in: ingate;
        out: outgate;
endsimple


module Mobilityscenario
        parameters:
                numberOfHosts:const,
                msgBufSize:const,
                maxHops:const,
```

```
            totalMaxHops:const,
            retransmissionInterval:const;
    submodules:
        dataCollector: DataCollector;
            display: "i=monitor;p=50,206;b=32,32";
        Hosts :  Host [numberOfHosts]
             gatesizes:
                inputs[numberOfHosts], outputs[numberOfHosts];
        engine: Engine;
            display: "i=cogwheel;p=50,50;b=40,24";
        simController: SimController;
            display: "i=bwgen;p=50,132;b=34,34";
    connections nocheck:
        engine.outgate --> engine.ingate;
    display: "p=10,10;b=1000,1000;o=#cfedfe";
endmodule

network mobilityscenario : Mobilityscenario
endnetwork
```

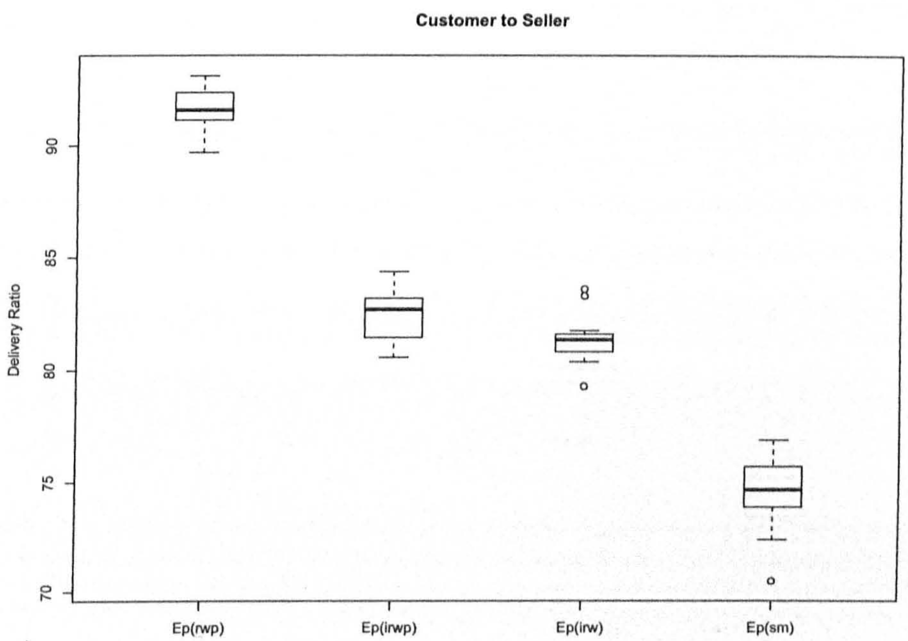
Appendix K

Epidemic

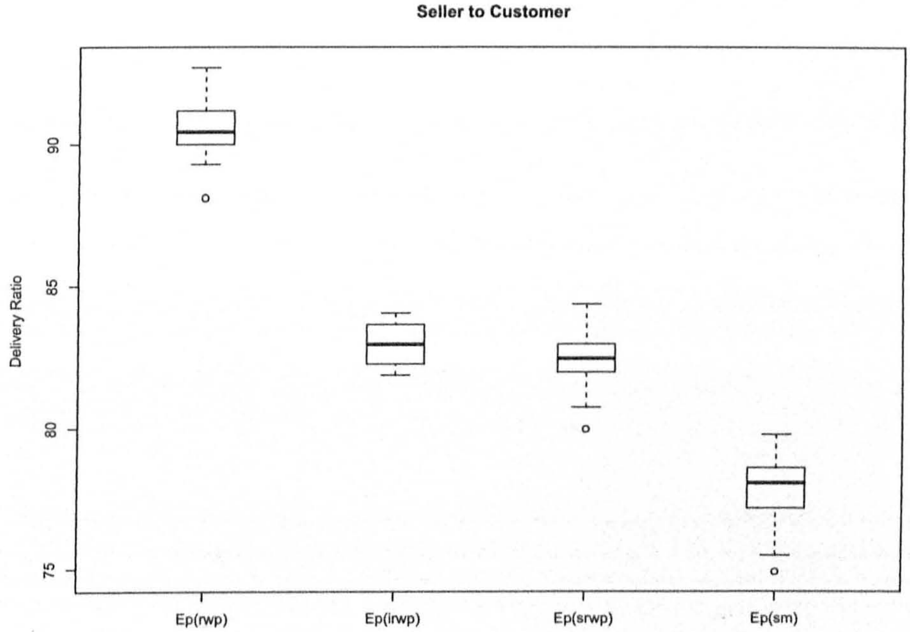
K.1 Delivery Ratio

K.1.1 Customer to Customer

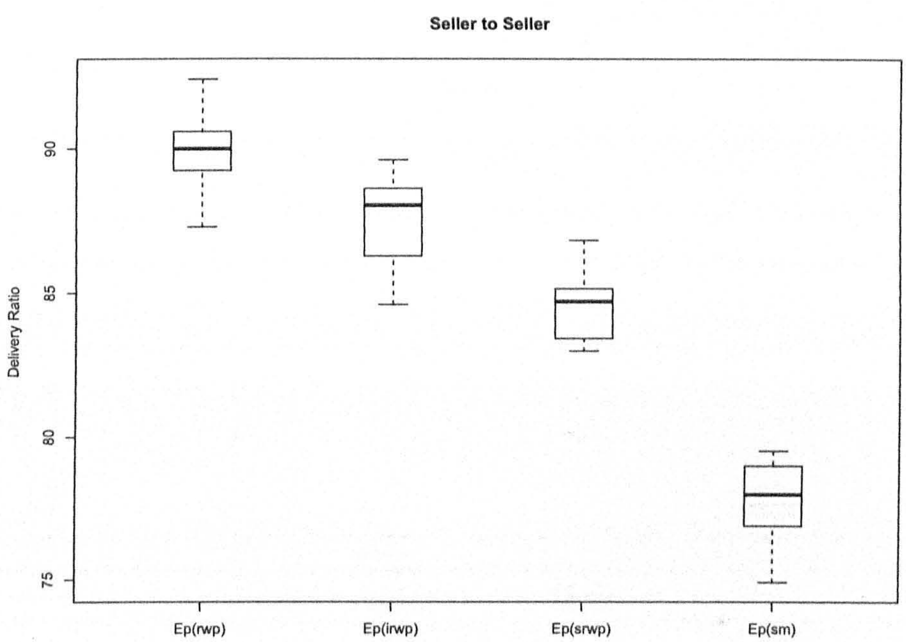
K.1.2 Customer to Seller



K.1.3 Seller to Customer

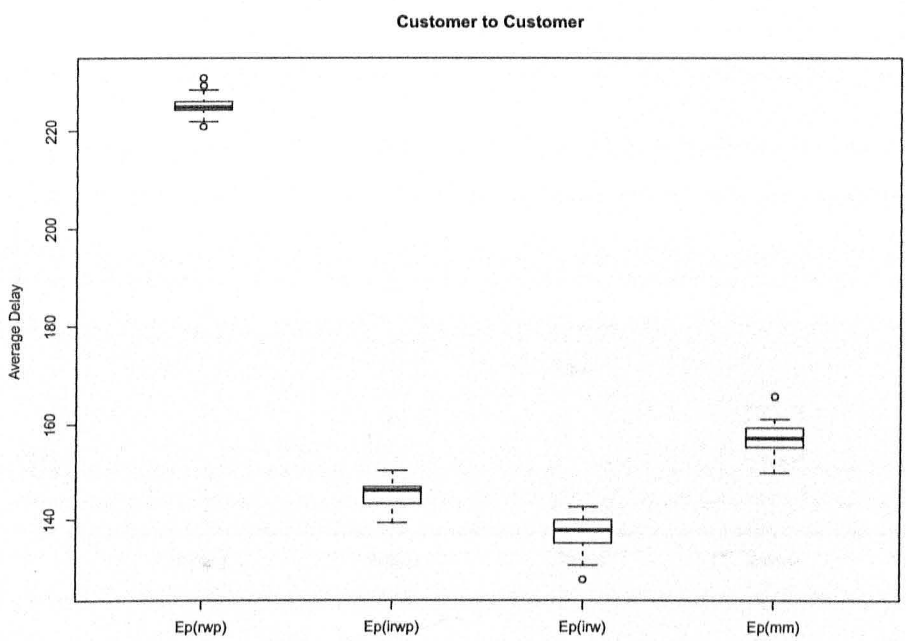


K.1.4 Seller to Seller

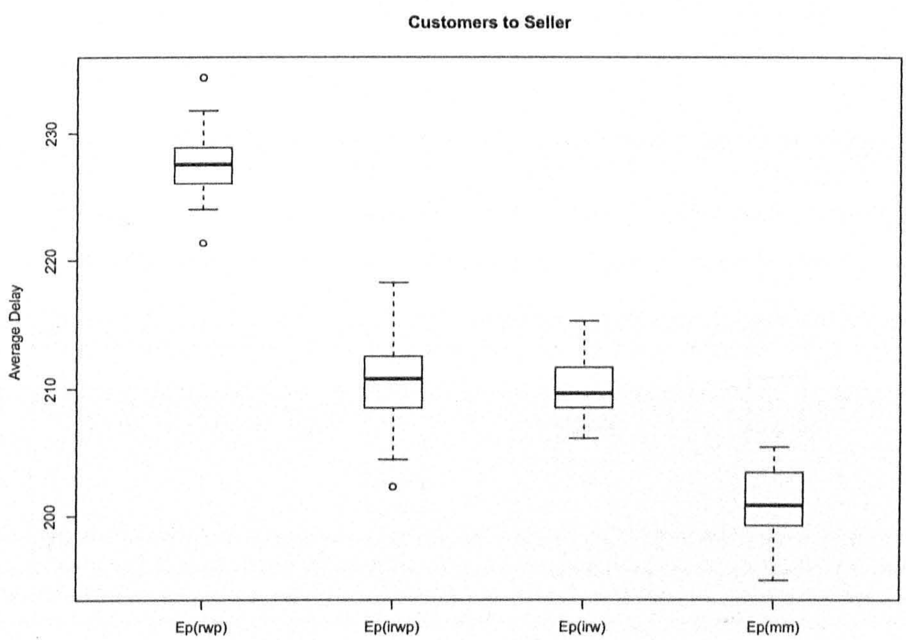


K.2 Epidemic: Average Delay

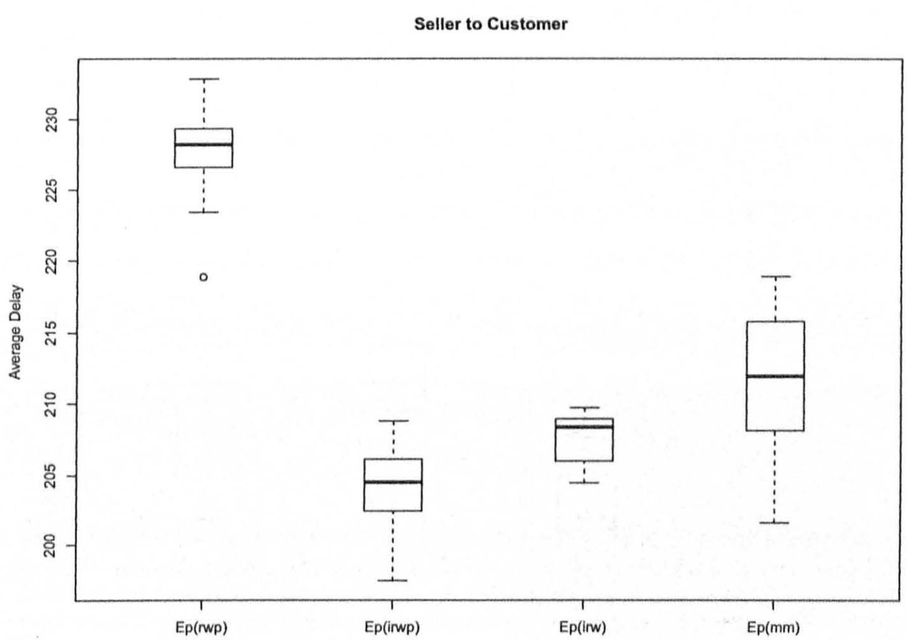
K.2.1 Customer to Customer



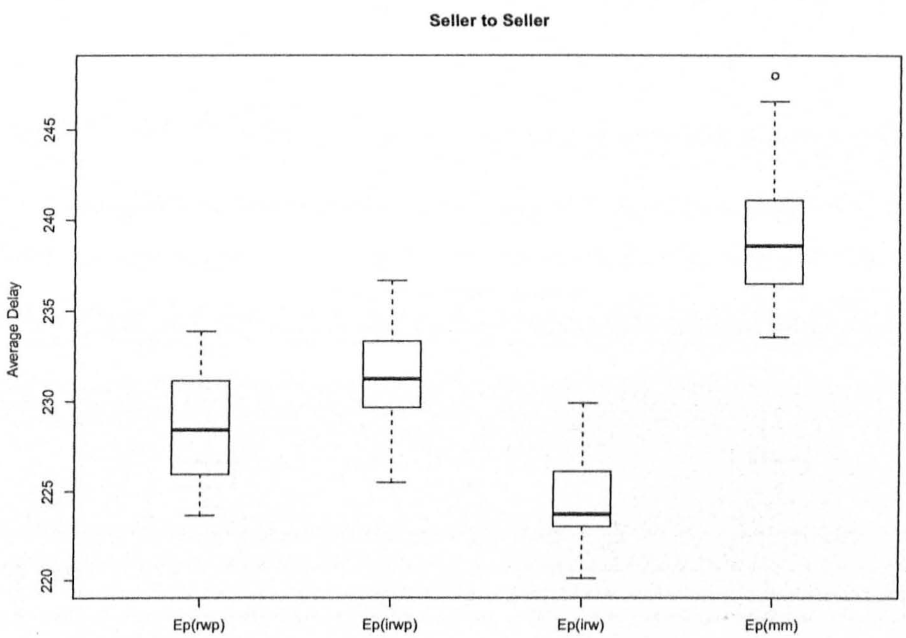
K.2.2 Customer to Seller



K.2.3 Seller to Customer



K.2.4 Seller to Seller

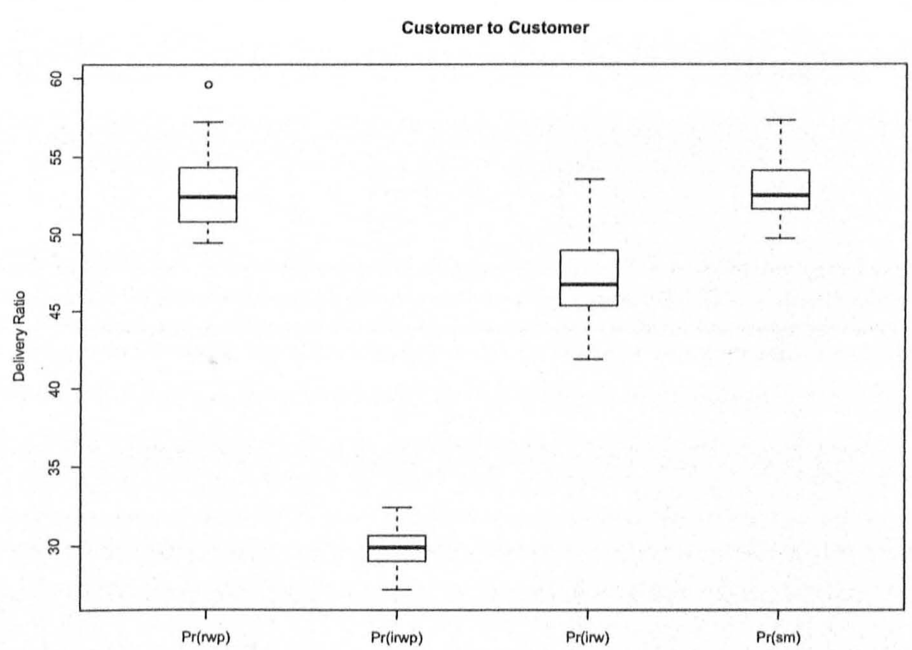


Appendix L

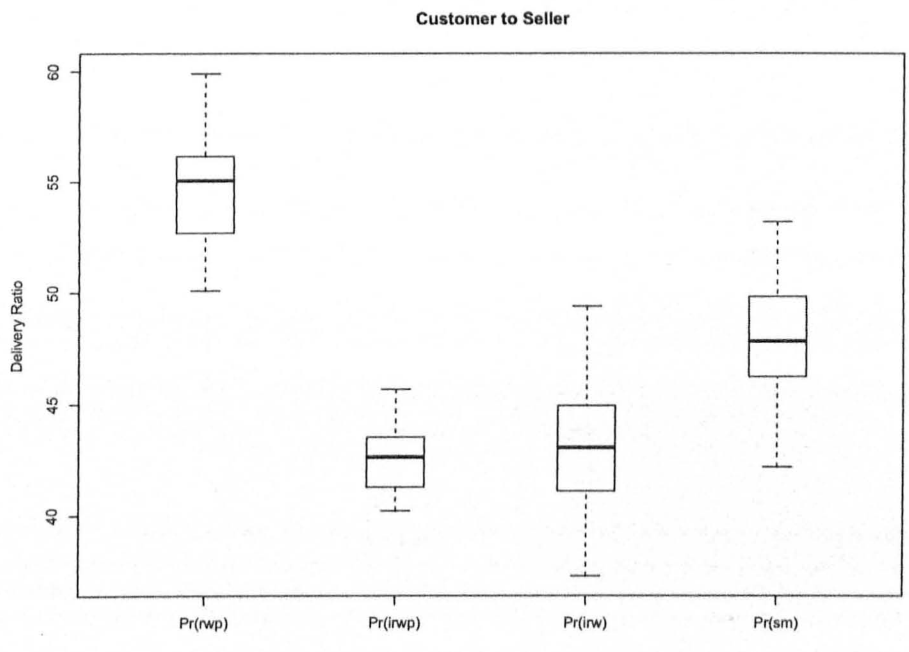
Prophet

L.1 Delivery Ratio

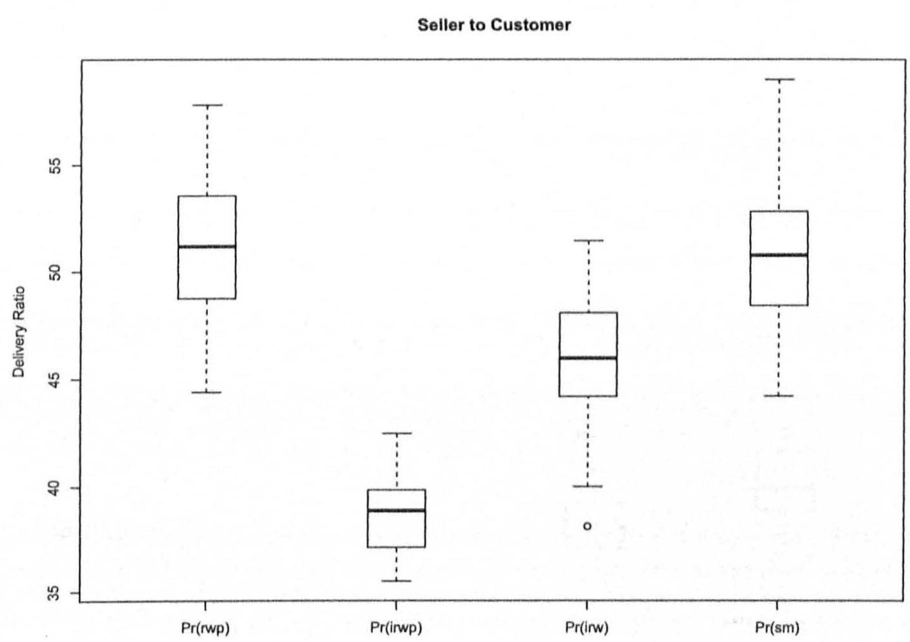
L.1.1 Customer to Customer



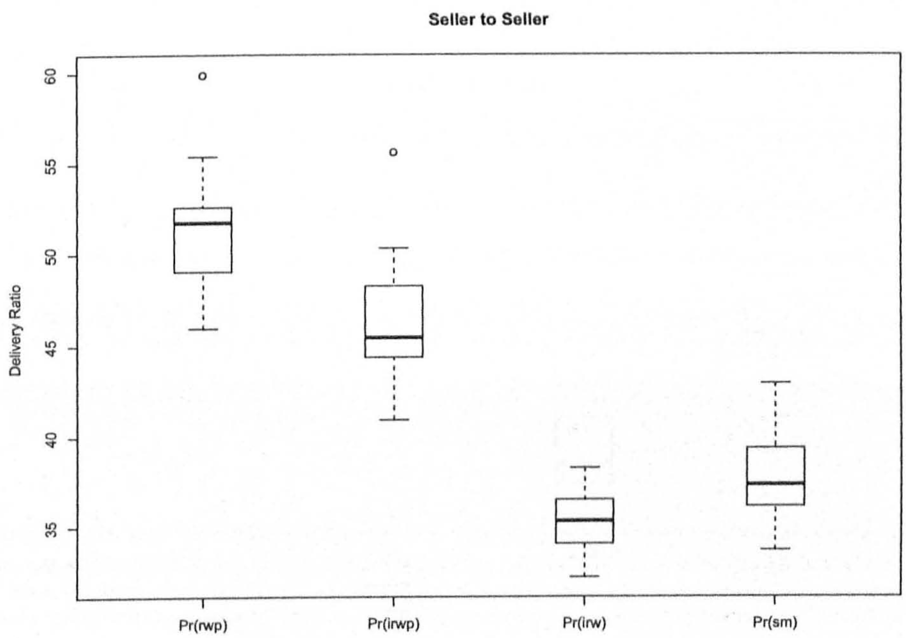
L.1.2 Customer to Seller



L.1.3 Seller to Customer

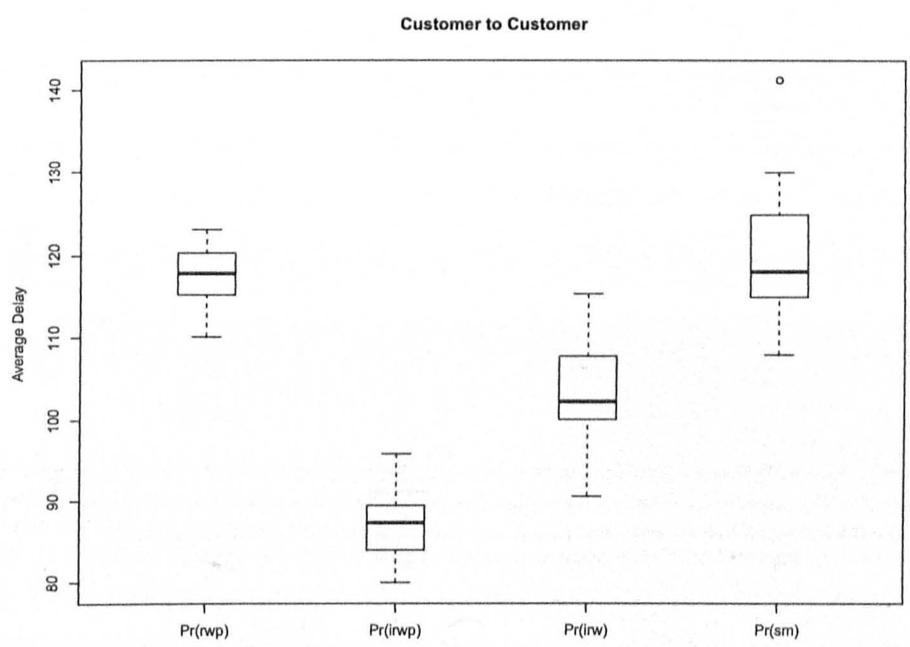


L.1.4 Seller to Seller

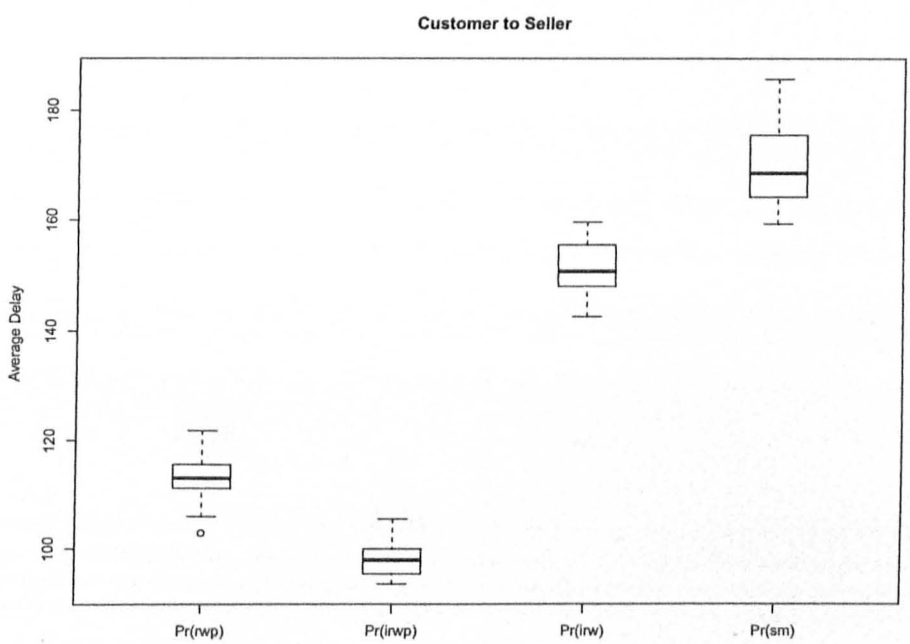


L.2 Prophet: Average Delay

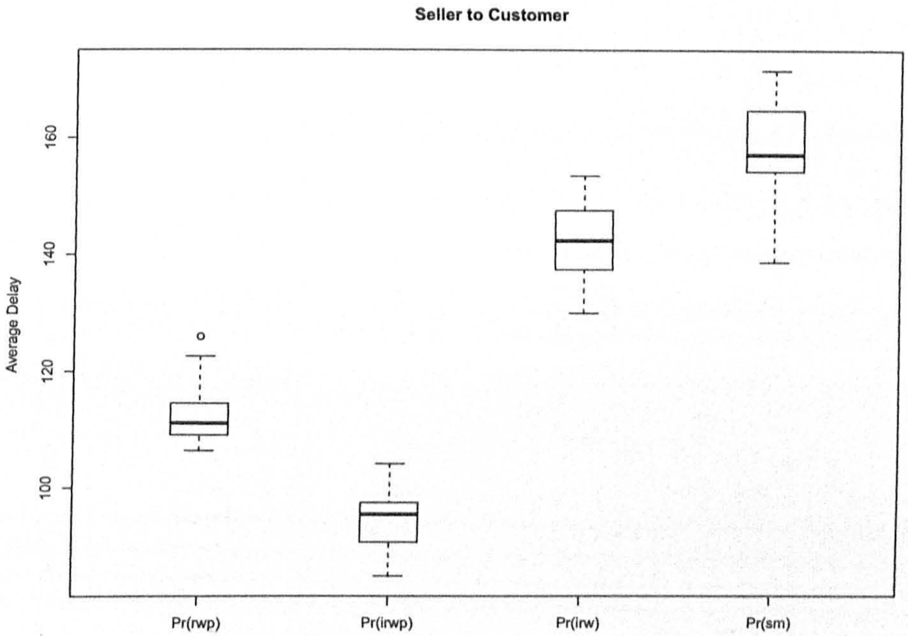
L.2.1 Customer to Customer



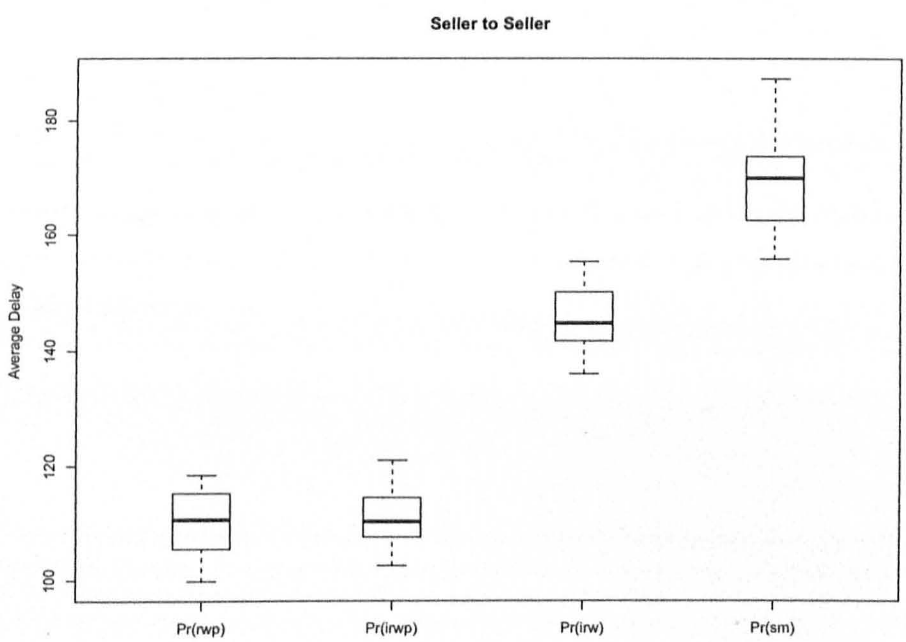
L.2.2 Customer to Seller



L.2.3 Seller to Customer



L.2.4 Seller to Seller



Only two things are infinite,
the universe and human stupidity,
and I'm not sure about the former.

Albert Einstein