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och systemteknik**

Opportunistic Networking: Mobility Modeling and Content Distribution

LJUBICA PAJEVIĆ

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School of Electrical Engineering
KTH, Stockholm, Sweden

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Abstract

We have witnessed two main trends in recent years that have shaped the current state of communication networks. First, the Internet was designed with the initial idea to provide remote access to resources in the network; today it is overwhelmingly being used for content distribution. In addition, the community of content creators has evolved from a small group of professionals into a global community where every user can generate his contents and share it with other users. Second, the proliferation of personal mobile devices, such as smartphones and media tablets, has altered the way people access, create and share information, leading to a significant migration from wired to wireless networks and raising user expectations for ubiquitous connectivity. These trends have incited research on new communication modes and in this thesis we consider a specific mode, namely opportunistic networking.

Opportunistic networking is a communication paradigm that utilizes intermittent connectivity between mobile devices to enable communication in infrastructure-less environments, and to provide complementary transport mechanisms in wireless networks where infrastructure is present. The thesis focuses on two main topics: understanding and modeling human mobility, and opportunistic content distribution.

Mobility modeling is one of the key issues in opportunistic networking research. First, we discuss the structure of human mobility and introduce a framework to study mobility at different behavioural levels. We propose a queuing model, denoted by *meeting-point* model, for pedestrian mobility in smaller urban areas, such as city squares, parks, shops or at bus stops. The model is also a contribution to the second topic we address in the thesis, since we will use it to study characteristics of content distribution in smaller areas. We envision this model as a building block in a library of analytical models that would be used to study the performance of pedestrian content distribution in common scenarios of urban mobility. Furthermore, we show how the proposed model can be used to build larger, more complex models.

In the area of opportunistic content distribution, we apply both analytical and simulation-based evaluation. We empirically study the performance of epidemic content distribution by using real-life mobility traces and investigate the fitness of a homogeneous stochastic model to capture the epidemic process.

In addition, we present the design, implementation and evaluation of a mobile peer-to-peer system for opportunistic networking and discuss some promising application scenarios.

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1 Introduction

Seize any opportunity, or
anything that looks like an
opportunity.

NASSIM N. TALEB

The way people share and obtain information has always had a major impact on human society. Enabling nearly ubiquitous reachability to various types of information, enhanced by powerful communication and computing resources, and intuitive user experience, mobile devices such as smartphones and media tablets have quickly become a part of our everyday lives. The proliferation of these devices has not just altered the way we communicate and interact, but it has also led to a significant innovation of services and is likely to further reshape the industries such as entertainment, commerce, healthcare and education. Exploring the possibilities to utilize their communication capabilities, as well as the fact that they are carried by their owners throughout the day, this thesis focuses on *opportunistic networking*. Before delving into explaining this concept, let us reflect on the current state of communication networks and future trends that are inviting solutions for new communication modes.

Mobility as enabler

Initially designed to carry voice traffic, today mobile wireless systems are predominantly used to transport data, owing to fast adoption of converged mobile devices. In the recent years, mobile data traffic has increased at unprecedented scale. According to [1], mobile web traffic represented around 17% of global web traffic in September 2013, while that share was less than 1% in 2009. Enabling services and experiences formerly available only in the wired domain, mobile access and ubiquitous connectivity have become not just a need, but a necessity for many network users. New technologies such as wireless machine-to-machine communication are also emerging and contributing to increased traffic. Cisco Visual Networking Index [2] predicts continuous growth, with mobile data traffic yielding 13-fold increase between 2012 and 2017 and reaching 11.2 exabytes per month by 2017. Deployment of next-generation mobile networks may not be able to follow this trend, and the traffic demand is likely to urge mobile operators and service providers to consider alternative networking solutions.

Users as contributors

In a similar way as mobile systems have evolved from voice to data carriers, the Internet has changed its nature over the decades. The main ideas for both systems revolve around the concepts of telephony which was, at the time of their development, the only example of successful global-scale communications. The nature of the Internet is conversational, since it was designed to provide one-to-one communication between end points in the network. However, the rise of the World Wide Web, and later Web 2.0 applications, caused a dramatic change— it is now overwhelmingly used for content dissemination, i.e. delivering messages to more than one recipient, while the community of content creators has grown from a small group of professionals to a global community where every user can generate his contents. The shift has become even more pronounced with the emergence of social networking and mobile web. Massive amounts of data are being generated and consumed: statistics show that users of the most popular photo-sharing sites (including Facebook, Instagram, Snapchat and Flickr) upload around 500 million pictures daily, while 100 hours of videos and 11 hours of sound are uploaded every minute to Youtube and Soundcloud. These changes suggest requirements for new architectures based on a content-centric rather than a host-centric approach and several proposals are readily available, e.g., NetInf [3], and CCN [4].

Opportunistic content distribution

Opportunistic networking is a communication paradigm based on proximity of mobile users and their capability to store data on their devices, carry it through their mobility and forward it to other users they meet. An event when the devices of two users are found within direct transmission range is called a *contact opportunity*. When such an opportunity arises, two users are able to establish wireless connection (e.g. WiFi or Bluetooth) to exchange data in ad hoc peer-to-peer manner and based on user interests.

Intermittent connectivity, frequent topology reconfiguration and often lack of end-to-end paths between users, are considered as normal features of the network instead of exceptions. This communication mode, however, can be useful for content delivery characterized by a low degree of interactivity, such as podcasting, messaging, and data collection. We recognize this approach has several advantages compared to current (wireless) distribution networks.

- *Infrastructure independence*

With the basic idea of exploiting intermittent contacts, which occur owing to users' mobility, this approach can solely rely on direct communication between devices, without the need of infrastructure support. Therefore, it can be seen as a viable solution to enable communication in cases where infrastructure is absent (rural and remote regions), (temporarily) down due to a failure,

for instance in case of natural disasters, or its use is undesirable (e.g. using roaming services for mobile subscribers).

- *Scalability*

In contrast to infrastructure wireless networks, increasing the number of participating users is likely to improve the system performance. Popular contents will be replicated more often and available at many users; this feature could be beneficial for mobile operators for diverting a part of the traffic from a cellular network to opportunistic carriers.

- *Network neutrality and censorship*

Network neutrality argues that users should be able to access any contents and use any applications they choose, without restrictions or limitations imposed by their governments or Internet service providers. With numerous examples in the recent events, content censoring and service blocking could be recognized as the worst deviation from neutrality. The decentralized nature of opportunistic networks makes imposing such restrictions very difficult.

- *Locality awareness*

Intrinsically based on users' ability to communicate whenever their devices are within direct communication range, this approach fits well for enabling location-based services and applications. Mobile search queries already represent a large portion of local searches; thus exploiting locality and opportunistic contacts is a promising solution for distributing locally relevant contents.

- *Privacy preserving*

Assuming infrastructure-less topology, the distributed approach of opportunistic social networking is favourable for sharing content with trusted peers only, and without mediation of any centralized entity or service provider.

Thesis scope and outline

In this thesis we address several aspects of mobility-assisted opportunistic content distribution in urban areas. The main contributions are the following.

- *System design and implementation*

We present the architecture and design of a content-distribution system based on a publish/subscribe paradigm and peer-to-peer communication between mobile nodes. While our focus is on the mobile ad hoc domain, the architecture also supports seamless content dissemination between the wired Internet domain and the ad hoc domain. The system design addresses two main issues: 1) the structuring of contents that enables efficient lookup and matching and 2) a content solicitation protocol for discovery and retrieval of contents. We have also implemented the design on Android mobile devices and performed evaluation of the system performance.

This work was published in the reference [5]. The author of this thesis has contributed by actively participating in discussions on the system design, and applications presented in 4.7; the concept for the middleware structure and the solicitation protocol was developed and implemented by Helgason. The author has also participated in the experiments carried out for testing the middleware.

- *Characterizing and modeling mobility*

First, we discuss the structure of mobility and introduce a framework to study mobility at different behavioural levels. Then we propose a queuing model for pedestrian mobility to study characteristics of content distribution inside smaller areas. We assume that the mobility of nodes does not affect their connectivity and focus on how queueing of nodes affects content distribution. We also show how a model for smaller spaces can be used to build larger, more complex models.

The author of this thesis contributed to formulating the framework to characterize mobility according to the three-level structure, as described in chapter 5. The initial work on the analytical queuing model proposed in chapter 6 was published in [6]. The model was developed by the authors of the aforementioned publication; the author of the thesis has performed the model analysis by means of simulation as well as the analysis of the framework proposed in the same chapter.

- *Empirical and analytic evaluation of content distribution*

We empirically study the performance of content distribution by using real-life mobility traces and investigate the fitness of a homogeneous stochastic model to capture the epidemic process of content spreading.

The contribution of the thesis' author is the statistical analysis of the mobility data and empirical evaluation of epidemic content distribution presented in chapter 7, while the stochastic model for epidemic content distribution presented in 7.1 was developed by the other two authors of the publication [7].

This rest of this thesis is structured as follows. In chapter 2 we give a background overview and discuss related work, Chapter 3 gives examples of application categories that can be built on top of an opportunistic system, while chapter 4 presents an overview of the design of a mobile middleware for opportunistic content distribution. In chapter 5 we study the structure and characteristics of human mobility, and following that, we propose our analytical model in chapter 6. We evaluate epidemic content distribution, both analytically and empirically in chapter 7. Chapter 8 concludes this thesis and presents directions for our future work.

2 Background and related work

Since the invention of the Aloha system [8] in 1970s, wireless networking has become increasingly popular both among users and in the research community. During the last two decades, the design of wireless networks started focusing on enabling mobility. Generally, the structure of wireless networks can include fixed nodes, *gateways* and *base stations*, that act as bridges between the wireless and wired domain, or it may comprise only mobile network nodes. In the first case, mobile nodes associate and communicate with the base station that is within their transmission range; in the latter case, networks are configured dynamically, in a decentralised manner when nodes discover neighbors in their vicinity. Each node then can act as a mobile router to forward messages, thus forming multi-hop paths between two remote nodes. These networks, commonly known as mobile ad hoc networks (MANETs), were proposed as a solution to complement infrastructure-based wireless networks and allow mobile users to access Internet services or communicate directly with each other when they are outside of the coverage area of cellular or WiFi networks. Research efforts on MANETs have resulted in a large body of work addressing a number of technical challenges, such as resource-efficient routing, fast neighbor/service discovery, low energy consumption, cooperation incentive mechanisms, and so on. The practical use of these networks, however, remains limited to closed networks and controlled deployment, for instance in sensor networks, and tactical mobile networks. The main inhibitor of wider usage is that routing algorithms strongly rely on the existence of reliable end-to-end paths between users and low-delay round-trip times, which often does not hold due to node mobility.

2.1 Delay-tolerant networking

Delay-tolerant networks (DTNs) [9] introduce a different communication paradigm, aiming to cope with intermittent connectivity. Sometimes also labelled as *disruption-tolerant*, DTNs are designed to operate in so-called *challenged* environments, characterized by long delays and disconnections occurring, most often due to node mobility, but also as a result of node failures, power management (unsynchronized wake-up times), or unreliable communication channels. Examples are interplanetary communications [10], sensor and actuator networks, military and disaster-relief deployments, provision of Internet access to developing and rural regions [11, 12], and different systems for peer-to-peer communication between mobile devices carried by humans, which is central to our work.

The DTN architecture [13] comprises a network of independent (heterogeneous) partitions, with only occasional communication opportunities among them. To support heterogeneous transport protocols of different network partitions, the architecture specifies an overlay, called the *bundle* layer, which operates above the transport layer, and the format of variable length application data units—bundles. One of the key challenges is the delivery of a message, between source and destination, since the partitions may be disconnected for indefinite periods of time. Communication in such a network is asynchronous and based on a *store-(carry)-and-forward* approach, with nodes delivering bundle messages when an opportunity arises, or according to some time schedule. Messages are transported in a usual hop-by-hop fashion; however, if the connection to the next hop is unavailable at some intermediate nodes (or the source), the message will be stored locally until the connection is re-established. In addition, different hops may rely on different transport mechanisms. This concept of message forwarding, as well as a few other DTN concepts, has been adopted in the design of *opportunistic mobile networks*, which unlike that of traditional examples of mobile ad hoc networks, takes into account frequent link outages and network heterogeneity as normal features, rather than treating them as states of network failure.

2.2 Opportunistic mobile networking

The term *opportunistic* networking is generally used in reference to mobility-assisted communication between mobile devices (e.g. smartphones and media tablets), carried by humans during their daily routines. These devices are often equipped with powerful computing resources, ample storage and multiple wireless interfaces (WiFi and Bluetooth). Such capabilities can be efficiently exploited to enable direct communication without support of infrastructure. Whenever two devices are found within each other's transmission range—in the networking literature, this event is called a contact opportunity—they are assumed to be able to establish a wireless connection to exchange data. In opportunistic networking scenarios, we usually assume highly dynamic network topologies or sparse node densities, insufficient to maintain end-to-end connectivity. Thus, the network is formed as a series of pair-wise contacts.

We acknowledge that, while this type of communication shows ample potential for various applications, it may be unsuitable for those which are tightly constrained by short time delays (audio/video streaming), or applications that dependent on end-to-end transport connections (transport layer based security mechanisms). Thus, common examples of compelling use-cases include distribution of bulk or user-generated data in urban areas, location-based services, mobile gaming, and providing Internet access in rural/developing regions. Considering the shift from the host-centric networking paradigm to content-centric, we envision mobile content distribution based on users' interests as a promising service in urban areas.

The work in this thesis revolves around the concept of opportunistic peer-to-peer podcasting, described in [14, 15, 16], and belongs to the scope of the Podnet project [17]. Podcasting is a method of distributing media contents, usually audio or video files, in a publish/subscribe manner. On the server side, content items are released episodically and published through a *feed* that identifies the topic; on the client side, subscribers use an application that periodically checks the feed and downloads newly published items. In chapter 4 we present the system design for a publish/subscribe system in challenged environments, by specifying the middleware architecture and protocol design, and the implementation of key components.

Recently, there has been a number of systems for opportunistic information sharing proposed and implemented as experimental testbeds. The previously mentioned DTN architecture is described by IETF document RFC 4838. Herein we give a brief overview of several systems and highlight conceptual differences between their architectures and ours.

- *Haggle* [18] is a data-centric architecture for mobile devices, which decouples application functionality from the underlying network technology to support applications to operate seamlessly across different networking environments, that is, in infrastructure-supported, as well as in infrastructure-less setting. This is achieved by a mechanism for just-in-time late-binding of network interfaces, protocols and names. When infrastructure connectivity is unavailable, applications are bound to interfaces that enable node association in ad hoc mode (e.g. WiFi or Bluetooth). The data format in Haggle specifies data objects described with attributes, each attribute consisting of type and value pairs and allowing for data searches both locally between different applications on the same device, and between peering nodes. Unlike in our system, this data structure is not hierarchical. Another major difference is that Haggle implements push-based data transfers, whereas the solicitation protocol in our architecture is pull-based. Haggle also follows the Podnet system in time [14].
- *BlueTorrent* [19] is a peer-to-peer opportunistic file-sharing application for Bluetooth enabled mobile devices. The concept of distributing large files by dividing them into small chunks follows our approach. The system design considers the optimal chunk sizes, and the parameter configuration to minimize peer- and content-discovery latencies. BlueTorrent, however, relies on Bluetooth, while our design is not restricted to a specific wireless technology and can potentially exploit any available ad hoc connection.
- *Mobitrade* [20] is a system for content dissemination, built on top of a DTN architecture. Assuming non-altruistic nature of users, the design aims to deal with their inherent tendency to obtain contents of their own interest, but do not wish to contribute to the entire system by serving other users. Mobitrade architecture proposes a trading mechanism that allows a node to buy, store and carry content for others, so that it can later exchange it for contents it

is personally interested in. This approach largely relies on the initial work on wireless podcasting [16], which our system is also built on, thus sharing some similarities, e.g. the concept of channels.

In this thesis we will concentrate on networks of pedestrian users; however, in the next chapter we will give an overview of most common use cases, some of them assuming other types of mobility, e.g. vehicular.

2.3 Mobility

Recognizing that mobility is an integral part of opportunistic mobile systems, many researchers have been seeking ways to accurately capture human movement patterns. An extensive survey of mobility models is given in [21]. While this topic, from the viewpoint of networking community, has gained most interest relatively recently, in some other fields, such as urban and transportation planning or epidemiology, it has been studied for decades [22].

Human mobility can be structured in three behavioural levels: strategic, tactical and operational [23]. The *strategic* level decisions include choice of activities an individual wants to perform, such as going to work, shopping or for outdoor activities, thus describing daily movement patterns. Based on the set of activities and the time available, the *tactical* level focuses on activity scheduling and route-choice, which can be the shortest or fastest path to destination, depending on the environmental factors (e.g. obstacles on the path or congestion). The physical process of human movement is described on the *operational* level. This level considers walking or driving speed, interaction with other nodes due to collision avoidance and queueing.

Each of the structural levels has a specific impact on the performance of opportunistic mobile systems. The strategic and tactical level decisions affect the distribution of time between two consecutive meetings of specific nodes—the inter-contact time—a crucial parameter for most forwarding protocols since it directly determines the message delay and the probability of successful delivery. Decisions taken on the operational level can affect the node connectivity and durations of contacts, which determine the amount of data that can be transferred and even the existence of the multi-hop path between distant users communicating over relay nodes.

From the perspective of communication networking, most of the research efforts in mobility modeling consider mobility on the tactical and strategic level. Currently popular models characterize spatio-temporal properties of human mobility [24, 25, 26], or focus on social aspects [27, 28]. Detailed operational-level mobility modeling, such as in [29, 30], has drawn less attention. In contrast to this, the operational mobility has been thoroughly studied for planning emergency and evacuation strategies, where capturing the properties of both collective pedestrian flows as well as the individual movements is of high importance, but also for

purposes such as designing and dimensioning public spaces with respect to comfort. Numerous analytic models have been developed and they often provide better approximation of human movement than the models commonly used in networking.

Modeling mobility analytically at all three levels with a single, comprehensive model is rather difficult, if not impossible. Thus, the actual scenario that is investigated should determine which characteristics of mobility are necessary to capture and which other characteristics can be abstracted away from the model to avoid unnecessary complexity.

3 *Use cases for opportunistic communication*

In this chapter we describe some common scenarios we believe may benefit from opportunistic communication. The aim is to further motivate our work, and also to explore the space of possible use cases as well as the challenges and research questions they arise.

Distributed vehicular data sensing

With the growing availability of user-generated data, crowdsourcing is becoming a valuable way of gathering information, both for users and service providers. One of the currently most exploited sources of data is floating car data (FCD), which includes positioning data such as GPS localization, information about cellular handoffs of mobile devices, and coverage of WiFi networks. FCD together with user-provided updates can be used to improve real-time traffic estimates. Currently, there exists many infrastructure-based solutions, (such as Waze [31]); however, they require centralized data processing, accompanied with significant computational complexity, and non-negligible latencies. In this context, opportunistic vehicle-to-vehicle communication can be beneficial for faster gathering, processing and disseminating traffic updates in a distributed fashion. It should be noted that the high vehicle densities needed for opportunistic communication to be feasible and statistically meaningful restrict the potential use to urban areas. Information about traffic conditions could be used locally by the vehicles, for example, to take driving decisions at intersections, or by dynamic traffic lights to adapt maximum speed limits and green/red light periodicity to the actual level of traffic. This application can additionally extend into the wired domain, if the information is propagated to a central controller, and exploited to derive better estimates of the overall road traffic and to inform drivers about the shortest route to destination.

Smart cities data sensing

Similarly to the previous case, mobile devices can be used to collect sensing data beyond positioning and network connectivity information. Smartphones are already equipped with a rich set of powerful (and inexpensive) embedded sensors, such as camera, microphone, GPS, accelerometer, gyroscope, and so on. New features including step counters, movement, pressure, temperature and humidity sensors

are being added. These features can be exploited for generating fine-grained maps of city areas with measured levels of noise, reporting infrastructure problems (e.g. holes in streets) and public safety issues, measuring flows of pedestrian and crowds for the purpose of urban planning, positioning inside buildings, shopping-malls and airport terminals.

Local advertising in urban areas

This case includes city scenarios in which shops, restaurants and other businesses want to advertise their products or services to pedestrians that cross specific areas. The main application is dissemination of data either to any user in the scenario, or to a specific group of users. Examples are users who visit a museum or a tourist site and opportunistically receive information related to the visited area, or a local shop that advertises its products to a target customer group. Users then spread the information in the visited area, incrementing the visibility of the services and businesses.

Opportunistic social networks

Another application in urban environment is opportunistic social networking. Groups of users interested in exchanging delay tolerant data, such as music files, images, videos and personal profiles or even messaging and mobile networking, are representatives of this scenario. The groups are formed based on the users' mutual interests— examples are groups of university students in the same class, groups of friends, conference attendees and people attending various public events. This type of social networking is also seen as advantageous with respect to privacy concerns when compared to social networks that require infrastructure and a support of some kind of centralized entity [32].

Opportunistic services in developing and rural regions

In contrast to urban scenarios where opportunistic networking can be used to support already existent infrastructure, this concept can be used to enable communication in developing and rural regions, which are characterized by very sparse or non-existent networking infrastructure.

An example is the DakNet project [11], in which data mules in the form of bicycles, motorcycles or buses that make regular trips to remote villages, transport data between isolated and unconnected areas. In DakNet, data is relayed over short point-to-point links between WiFi-enabled kiosks or personal devices and portable storage devices, called mobile access points (MAPs), mounted on and powered by a vehicle. When a MAP meets a kiosk, it uploads/downloads as much data as it can. Then, a MAP physically transfers data to a hub, and kiosks synchronize the data with other kiosks using the Internet. Apart from the developing regions, local population in rural areas can opt for opportunistic communication as an alternative to costly rural-broadband solutions.

4 System design

In the previous chapter we gave an overview of use cases an opportunistic content distribution system could support. This chapter introduces PodNet: a system architecture for opportunistic content distribution. We provide an overview of the system and discuss the two different application domains: the fixed Internet and the wireless ad hoc domain with opportunistic node contacts. The main focus of this thesis is on content distribution among nodes in the the wireless ad hoc domain. It is however important to realize that the PodNet design allows for seamless distribution of content between the wired Internet and the wireless ad hoc domain. Hence this chapter presents an overview of the full system design.

4.1 System overview

A general instantiation of the PodNet system can consist of three domains as shown in Figure 4.1. Content can be generated by servers or hosts in the Internet domain as well as by mobile devices in the ad-hoc domain. The Internet and ad-hoc domains are linked by gateways that assist in disseminating content between domains and perform any necessary translations or proxy services.

The system imposes a hierarchical structure on contents by organizing them into *feeds* where each feed consists of a number of *entries* (shown in Fig 4.2). The sharing of contents is based on a solicitation protocol by which a node solicits entries for one or more feeds from a peer (a peer node can either be a mobile device or a gateway to the Internet, such as an 802.11 access point). The content structure in the system allows for ease of searching and a higher hit rate of content queries than if they were made for individual unstructured contents. The system design does not assume a traditional network layer with point-to-point unicast routing. Contents are disseminated in the network by means of node mobility, sharing of local contents and a receiver-driven solicitation protocol.

Figure 4.2 illustrates the node design and the main components of our architecture. Applications access the services of the session layer through an API that the middleware exports. The API implicitly defines the content structure for applications and it allows them to publish/subscribe to content feeds. The design is composed of a set of modules that implement the API, content solicitation on behalf of the applications, service discovery and the solicitation protocol. The architecture also contains a convergence sub-layer for cross-layer interaction, particularly with

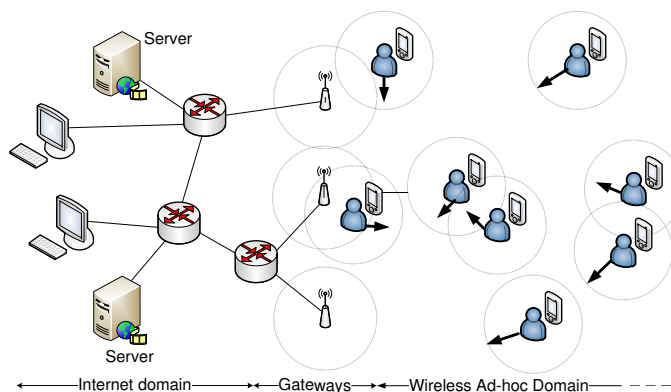


Figure 4.1: The system composed of servers, wireless gateways and mobile devices.

the underlying radio link such as WiFi or Bluetooth. Their architectures are quite different and thus the session layer architecture abstracts most of the details of the underlying radio and the heterogeneity of the networks away from the applications. The session layer assumes an underlying transport layer that preserves message boundaries, provides flow control and process-to-process communication above an optional network layer. Messages are delivered on a best-effort basis with no guarantee that entries on a particular feed will be delivered orderly to all receivers.

4.2 Content structure

Content addressing and organization adopts and extends the content structure of the Atom syndication format [33]. This format has primarily been used for publishing web-feeds and podcasts on the Internet. The content structure is quite generic and allows for more use cases than what has commonly been tried and it also maps nicely to the publish/subscribe semantics of our system. Contents are grouped into *feeds*. A feed is an unlimited container for *entries* that contain the actual data objects of interest. Each feed can have multiple entries published at different times by different entities. Both feeds and entries have associated meta-data. Each feed must contain a permanent globally unique ID assigned by the creator, a title and a timestamp that indicates the latest update. A feed can also contain optional meta-information such as author, subtitle and category. Similarly, each entry must also contain a globally unique ID, a title and a release timestamp and it can optionally have a range of other elements including zero or more *enclosures*. An enclosure is a single file attachment and would typically be an audio, video, or text file. To be able to efficiently transfer enclosures over the opportunistic contacts, we divide the enclosures into *chunks*, small data units of fixed size, which can be exchanged

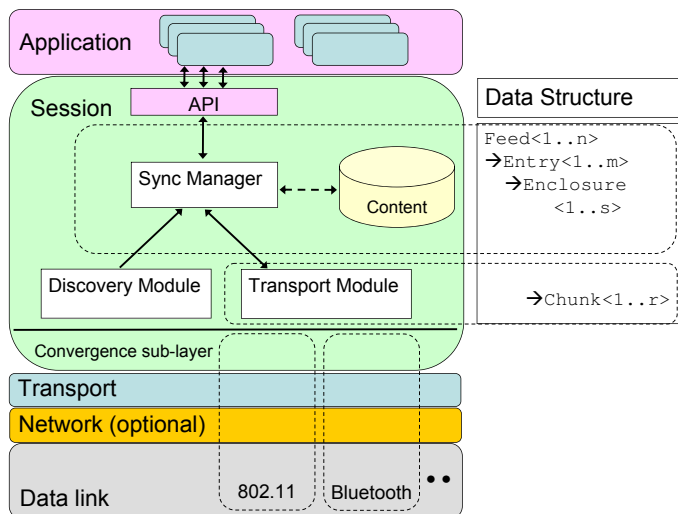


Figure 4.2: System architecture and data structures.

with high probability during a single contact of limited duration. Chunks are an extension to the Atom format and they allow an incompletely downloaded entry to be resumed with the same node or any other node that also has the entry (or parts of it). They are indexed starting from 1 and nodes can use these indices to resume interrupted downloads. If a chunk is only partially received from a peer (e.g. due to lost connection), it is discarded. The recommended chunk size is 16 kB which is found to tradeoff overhead and probability of incomplete reception well.

4.3 Interface

The API module implements the programming interface that applications use to access the services of the middleware. The API of our system is inspired by the Java Message Service (JMS) publish/subscribe API [34]. JMS however was designed for wired networks where dedicated brokers implement message delivery. The discovery of feeds also relies on centralized directory service. In our operating environment, central servers for performing these functions are not available. Instead, both resource discovery and message distribution are performed distributively with servers being replaced by *nodes*. Thus, in addition to the publish/subscribe functionality, we need to augment the API with a mechanism for feed discovery and for creating new feeds.

4.4 Synchronization and discovery

The *synchronization manager* processes contents from applications and solicits contents on behalf of them. If the local content database contains data that matches a subscription, the content is delivered immediately to the application. The manager prioritizes content solicitations such that different applications get a fair share of the network resource.

The *discovery* module is responsible for both neighbor and service discovery; it discovers neighbors that are running the service and decides which of these are feasible to associate with. The module is split across the main session layer and the convergence sub-layer. The latter implements neighbor discovery specific to the underlying radio subsystem and notifies the transport module when a neighbor has been discovered. This notification includes the `node-ID` and the `revision` number of the content database. The revision number of a node is incremented whenever new content is added to the database. This helps peers to determine if re-synchronization might be beneficial in case that nodes remain in range for longer durations, and thus avoid constant re-synchronization with all neighbors only to discover if any new contents have become available. The `node-ID` is a globally unique node identifier that does not have any particular structure. The only requirement is that nodes shall choose unique addresses such as a MAC address.

Our design does not assume any existing service discovery mechanisms and includes a basic mechanism by which nodes periodically broadcast `hello` messages to their link-layer neighbors, including the `node-ID` and the `revision` constructs described above. It is expected that in many cases nodes will support more advanced and efficient service discovery than the default `hello` method such as the service discovery protocol (SDP) in Bluetooth.

4.5 Transport module

The transport module performs session management and implements a request-reply protocol to download and discover available contents at a peer. Protocol messages are in XML format with the `message` element being the kernel of a protocol message. A protocol message has a single `node-id` element containing the ID of the message source and each message has a unique element that determines its type, given by one of the following message types: `hello`, `request`, `reply` and `reject`. All other elements of a protocol message are child entries for the header fields associated with the message type.

Session management

When a peer has been discovered by the discovery module, the transport module is notified which sends a `request` message to the peer to initiate a unilateral session for downloading. The request contains either a query for a particular feed entry or for meta-data to discover content availability. The peer sends a `reply` message,

establishing the session and replying to the query. Each download session thus consists of a client node sending request messages and a server node sending reply messages (or reject if the server is unavailable). The server is stateless with each reply message being independent of any previous requests. Processing a request only consists of verifying that the requested contents or meta-data exist and then to deliver them.

Content solicitation in our system is entirely pull-based. At the client, a typical session alternates between *discovery* and *download* states. In the former state, the client node queries the server for content-meta information whereas it downloads contents that match the subscriptions of applications during the latter state. With this approach, each node has full control of the contents it downloads and decisions are based only on the client state with the server being stateless. If the client node wants to filter the contents it solicits from a particular feed (such as only soliciting content published after a certain time) it first needs to solicit feed meta-information before it can directly request the entries available at the serving node that match the request criteria.

In general, a node can have multiple active sessions simultaneously with the node being either a client (when it is downloading) or server (when it is uploading) in each session. Note that the system does not explicitly enforce any mechanism to share download time between sessions; we simply rely on the mechanisms of the MAC layer to share the radio channel fairly. Ungraceful session termination (e.g. when nodes move out of range) is handled by a soft-state timer; if there is no activity from the peer for a certain time, the session is closed and any allocated resources are freed up.

Content solicitation

A **request** message contains the **bloom**, **selector**, **feed**, **entry**, and **chunks** elements. These messages are also used to query for meta-information to discover available contents at a neighbor and discover new contents, previously not known to the querying node. Discovering which previously known feeds or entries are available at a peer node is done efficiently by having each node maintaining a *Bloom filter* populated with the ID's of available feeds and entries at the node. A Bloom filter is a space-efficient data structure that provides a set-like representation of elements, requiring only a fraction of the space needed for a corresponding set with the actual elements. When a node receives a **request** with an empty XML **bloom** element, it delivers its Bloom filter in a **reply** message. After receiving the filter, the client node tests the ID's of its subscribed feeds or partially downloaded entries against the filter. Since false negatives are not possible, an ID not found in the Bloom filter does certainly not exist at the peer. Although false positives will occasionally result in requests being sent for ID's that are not available, the number of bytes transmitted to discover available contents is drastically reduced, thus speeding up the content synchronization process. A Bloom filter does not allow for iterating through the element it contains and thus it cannot be used to

discover previously unknown contents at a peer. The protocol therefore implements additional mechanisms for discovering previously unknown feeds and new entries on already known feeds.

The `selector` element of a request message can be used to solicit meta-information for contents that match a particular selection criterion given by a *content selector* that has the same semantics as the message selectors previously described in section 4.3. A *content selector* is a string whose syntax is based on a subset of the SQL92 conditional expression syntax [34]. A node that receives a `request` message with a `selector` as top-level element of a `request`, evaluates the selector on the attributes of each of its available feeds. The feed elements for which the selector evaluates to true are delivered in a reply message. Similarly, a selector specified inside a `feed` element will be evaluated against all entries of the specified feed and only those entry items that evaluate to true are delivered. An empty selector will match all feed/entry elements and those attributes not specified in the selector evaluate to true by default. Since nodes can have large content libraries, specifying a selector when discovering feeds can significantly reduce the amount of meta-data delivered in a `reply` message.

4.6 Implementation

We have implemented our system in Java for the Google Android OS platform. Our implementation is based on 802.11 in ad-hoc mode but we also intend to support Bluetooth in the future. The Android Java libraries (version 2.2) do not currently support the ad-hoc mode of 802.11 although this is supported by both the driver and the hardware interface on the HTC Hero device. Therefore, our implementation requires the device to be run in privileged user mode (i.e. rooted mode) so that the interface can be reconfigured to run in ad-hoc mode.

The middleware is implemented as an Android *service* which runs in the background and uploads and downloads data from peers that it discovers. Client applications can *bind* to the service and communicate with it by means of remote procedure calls (RPCs) through the publish/subscribe interface that it exposes. A client application wishing to receive a notification when an entry matching one of its subscriptions is downloaded, needs to implement and register a callback function that the service uses for notification. The interfaces for the service API and the application callback function are shown in listing 4.1. The remote methods exported by the service through the `IServiceAPI` interface are executed synchronously, thus blocking the local thread at the caller. In the service process, a method call is executed in a dedicated thread chosen from a pool of threads that is maintained by the Android system. The callback method in the `IClientCallback` interface is however executed asynchronously (specified by the `oneway` keyword) and therefore the service does not block when it notifies a client application.

The *discovery module* is implemented as two threads. One thread periodically broadcasts `hello` messages on a well-known UDP port and a listener thread waits for incoming `hello` messages from other nodes. The discovery module maintains a

Listing 4.1: Interfaces for the service API and the application callback function.

```

interface IServiceAPI {
    void publish(in String feedID, in Entry entry);
    void subscribe(in String feedID);
    void unsubscribe(in String feedID);
    void discover(in String selector);
    void undiscover();
    void registerCallback(IClientCallback cb);
    void unregisterCallback(IClientCallback cb);
}

oneway interface IClientCallback {
    void notify(in String feedID, in Entry entry);
    void discoveryNotify(in String availableContents);
}

```

contact history cache along with the `revision` number for each peer in the cache. When a new peer is discovered, the *discovery module* notifies the *transport module* which initiates a download session with the peer. If a peer, already in the contact history cache, is seen, the transport module is notified if the peer has obtained new contents since the last association or if there are new subscriptions locally.

The *transport module* implements both the client and server sides of a download session. The solicitation protocol is currently implemented on top of a simple transport protocol that implements message boundaries on top of TCP. The server side implementation listens on a socket and spawns a new session thread for each client. Similarly, if multiple nodes are in communication range the transport module can create a separate client thread for each session. Currently we set the maximum number of concurrent client and server sessions to 6 in total (3 for each). If a new node tries to associate when the maximum number of sessions is reached, the server sends a `reject` message.

The *content database* of the system is implemented as an *Android Content Provider*. Meta-information for all available feeds and entries is stored in a SQLite database and this information is accessible to all applications on the device through the `ContentProvider` and `ContentResolver` Android Java classes. The enclosures themselves (i.e. data files) are however not stored in this content database but in the corresponding Android Content Providers. Images, audio and video contents are for example stored in the Android `MediaStore` content provider. Thus, all media content published or downloaded by our system is available to all applications in a standard Android manner.

4.7 Applications

The opportunistic publish/subscribe service presented by the system architecture is quite generic and provides developers with variety of possibilities for application development. In this section we give examples of application categories that can

be built on top of our system. Those categories encompass applications that differ in their spatial scope, as well as in the involvement of users to the data generation and the data exchange.

Local quiz: With this application, users can opportunistically initiate a local quiz or a poll. When a user initiates a new quiz instance it creates a feed and publishes the quiz as the first entry. Participants subscribe to the feed and publish their answers as new entries on the feed. Information on available quizzes could also be distributed on a dedicated discovery feed. When participants come into communication range they exchange published entries and locally update their results. In the simplest scenario where no result aggregation is needed, each user can receive the answers from other participants and then, based on higher level logic, create its own representation of the quiz results.

Social networking: Many of the current social applications that are popular on the Internet (such as Facebook or Twitter) fit comfortably with the publish/-subscribe abstraction and can be extended into the opportunistic domain. Each user has a feed that followers subscribe to. Status updates, blogs or media files can be published as entries by the user. The actual data to be shared in each entry will be specified in the enclosure field, and users could for example define different feeds for separating content, e.g. an audio or a video feed. Applications falling into the social networking category are not expected to have any spatial limitations, thus the content can be spread opportunistically as long as there is interest in it.

Relaying sensor data: This category relates to applications that require transporting sensor data from devices in the field to a sink node or infrastructure network. Nodes that participate in relaying of data subscribe to feeds on which the sensors publish data.

4.8 System evaluation

The evaluation in this section is performed on identical HTC Hero A6262 mobile devices. These devices have a 528 MHz Qualcomm MSM7200A processor, a ROM of 512 MB and RAM of 288 MB and a Lithium-ion battery with capacity 1350 mAh. During our experiments, communicating nodes were stationary in an indoor office environment and placed within one meter from each other.

Energy consumption

We have measured the effect of our system on the battery life of the device. The Android system sends out an event notification (Intent) whenever the remaining life of the battery changes (in units of 1%). We have created a simple application that registers for these events and logs the time whenever the battery status changes. This way we can track how fast the battery is drained when various system services and applications are turned on or off. In Figure 4.3, we compare the battery profile for 5 scenarios: a) with the 802.11 interface turned off and our system not running, b) with the 802.11 interface turned on in ad-hoc mode but our system not running,

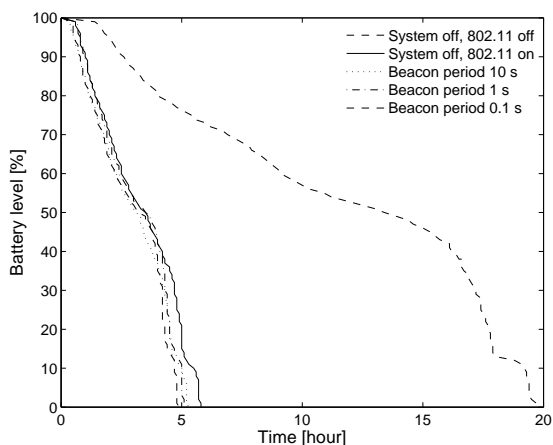


Figure 4.3: Comparison of battery profiles when 802.11 is turned on/off and our system is turned on/off.

and with our system running with the interval between `hello` messages set to c) 0.1 s, d) 1 s and e) 10 s. All measurements were performed on the same device with no other active devices in range at the same time. During all measurements the display backlight was turned on. This drains the battery faster than in normal mode but prevents the device from going into idle battery saving mode which reduces the comparability of our measurements.

From Figure 4.3, we clearly see that the 802.11 interface significantly increases energy consumption. Running our system (in idle mode, only sending `hello` beacons) in addition to the 802.11 interface does not add considerably to the energy consumption beyond what is required by 802.11. When beaconing every 0.1 seconds¹, the battery lasts approximately 40 minutes shorter than when the `hello` messages are sent every 10 seconds. We intend to add Bluetooth support to our system as well since it is significantly less power hungry than 802.11.

Solicitation protocol profiling

We have profiled our implementation of the solicitation protocol to verify correct behavior and assess performance. For our measurements we have instrumented the code with hooks where we stamp the system clock (which provides millisecond precision). During a measurement run we turn off logging and collect the measured timestamps into a list which is printed to a file after the code section being measured

¹This is the beacon period commonly used by 802.11 access points.

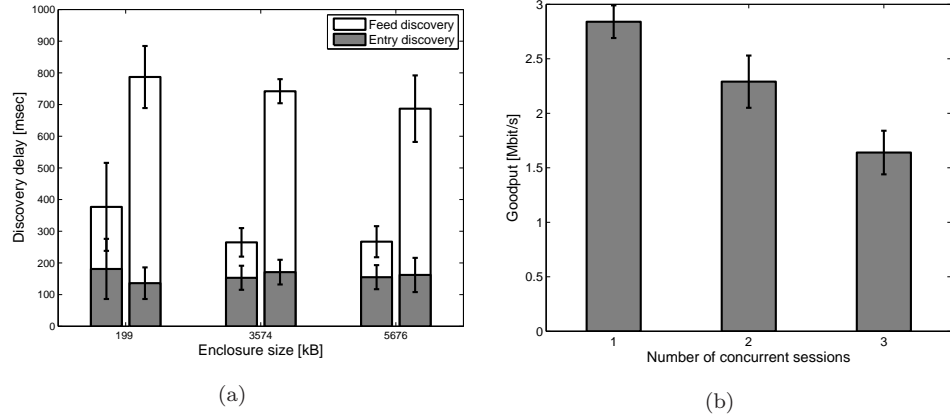


Figure 4.4: Profiling results for the mean feed and entry discovery delays. Each group of two bars contain results with one feed in the content database (left) and 100 feeds in the content database (right). (a) The mean goodput of a download session when the number of concurrent clients is varied between one and three. (b)

has completed running. This minimizes the effect of any I/O operations due to logging or measurements on our results.

As described in section 4.5, a typical download session consists of three steps: 1) the client discovers available feeds at a server, 2) then it discovers available entries for a given feed and 3) finally downloads the entry of interest. In Figure 4.4 (a) we show the mean feed discovery and entry discovery delay (steps 1 and 2). We have conducted measurements for three different enclosure sizes and for each enclosure size we conduct one set where the content database only contains the actual feed and entry of interest (left-side bars) versus the case when the database has 100 other feeds available (right-side bars). For each measurement we conduct 10 runs and in the figure we show the mean value and the standard deviation. The results confirm that the total discovery delay (i.e. the sum of the feed discovery and entry discovery delays) does not depend on the size of the downloaded enclosure. When the number of feeds in the content database increases, the feed discovery delay increases due to an increase in the number of bytes transmitted in the reply message (which contains the list of available feeds) and processing delay at the server. We see also that the entry discovery delay remains the same since the number of entries on the feed of interest is the same in all experiments.

Our implementation supports multiple concurrent download sessions and in Figure 4.4 (b) we show the average goodput of a session when the number of devices concurrently downloading is between 1 and 3. Our measurement setup is as follows. Between one and three nodes (referred to as clients) are within range of a single node (referred to as server) which publishes a single entry on a feed that the client nodes are subscribing to. When the client nodes receive the first `hello` message

sent by the server after the entry publication, the clients see that the server has new content and therefore simultaneously associate with it. The client nodes discover the entry and then download it and we measure the goodput G of each session as $G = B/T$ where B is the total number of bytes transmitted and T is the duration of the download session, i.e. the elapsed time from when the client discovers the node until it receives the full entry and enclosure.

Since the client nodes are being served concurrently, it is the responsibility of the MAC layer to share the radio channel between the download sessions. If the server would only support one session at a time the clients would be served sequentially and contention at the MAC layer is reduced. For a server that does not support concurrent sessions, the mean goodput for N sequentially served client nodes is given by $G_N = \frac{1}{N}(B/T + B/2T + \dots + B/NT)$, assuming that the client nodes are not further sharing the entry among themselves. For $N = 2$ and $N = 3$ we get $G_2 = 0.75 G_1$ and $G_3 = 0.61 G_1$. In our measurements we obtain the mean value $\bar{G}_1 = 2.86$ Mb/sec. Using this value in the expressions for G_2 and G_3 gives $G_2 = 2.13$ and $G_3 = 1.73$ Mb/s which are lower and higher respectively than measured values in Figure 4.4 (b). This indicates that serving nodes concurrently may not be beneficial when more than two nodes are interested in the same content. In our future work we intend to conduct measurements on an implementation where nodes are served sequentially to verify if this holds in practice.

4.9 Conclusion and discussion

We have presented a middleware architecture for mobile peer-to-peer content distribution. Content spreads via sharing and direct interest-based dissemination and our design includes a set of basic mechanisms for efficiently discovering and downloading content in opportunistic networks.

We have described the design and implementation of our system for the Google Android platform. The Java based environment provides a familiar environment with good support for most common OS primitives such as threads and concurrency, database and content storage and inter process communication through the Android service binding mechanism. Some features are however still missing, in particular support for the 802.11 ad-hoc mode (which needs to be implemented in native code).

We believe that our design is general and facilitates the implementation of advanced content-centric applications. There are however some issues that are not, or only partially addressed by our design. We do currently not address particularly the issues of privacy, security and power management. As we showed, the 802.11 interface draws significant power and it is probable that an implementation based on Bluetooth would be less battery demanding. Bluetooth however has other limitations, such as a long and inefficient discovery process and it also requires pairing of mobile devices, which often involves some level of user interaction. These limitations make Bluetooth ill-suited for mobile scenarios. Further, content dissem-

ination in our system is purely interest-driven and nodes do not cache or forward any contents beyond what they are privately interested in. As an extension of the system design, the authors in [35] consider several caching strategies and provide an extensive evaluation of the system performance.

5 *Characterizing mobility*

It is known that mobility of users greatly affects the performance of wireless systems [36, 37]. This becomes even more pronounced in opportunistic networks, where mobility is an integral part of the system. Moreover, the system depends on mobility for its operation. Data is carried by users through their movement; in cases where infrastructure is unavailable, (e.g. rural areas or disaster recovery scenarios) this might be the only way of transporting and forwarding data to disconnected areas. The purpose of this chapter is to introduce the theoretical background for the characteristics and the structure of mobility. We consider three different classes of mobility models and closely examine how their structure corresponds to the one we propose. Then, we illustrate how different application scenarios impose different requirements for modeling purposes.

5.1 Understanding and modeling mobility

Mobility is one of the key issues in opportunistic networking research, but unlike other important aspects of a system, it can only be studied and not engineered. Realistic representation of human mobility is essential for simulation and evaluation of system performance. However, deploying experimental testbeds and systems to obtain large-scale measurements is cumbersome and costly, yet the results often adhere only to specific scenarios and are difficult to generalize. Therefore, a common approach is to mathematically model mobility.

Maier and Rechtin [38] define a model as an approximation, representation, or idealization of selected aspects of the structure, behaviour, operation or other characteristics of a real-world process, concept or system. The aspects of real-world human movement that a mobility model needs to capture depend on the use of the model. Hence, it may be better to have several analytically tractable models for system studies, as opposed to one comprehensive model in its entire generality. Particularly, a modeler has to consider a number of aspects, including: the heterogeneous mobility of communication nodes, communication applications and corresponding network traffic, computational complexity and representativeness of a model. We rationalize this proposal in the next section, where we look more closely into the characteristics of mobility.

5.2 Structure and characteristics of mobility

Mobility of communication nodes is driven by many different means of transportation. Nodes that are carried by humans follow the means of transportation that we use in our everyday lives, including walking, bicycling, as well as travelling in cars, buses and trains; but nodes may also be mounted on vehicles with movements given by the mission of a journey.

Some characteristics are generally valid for mobile nodes. We can assume that the mobility takes place on a space with a given topography, such as a surface of an office floor, a grid of streets for a city area, or an interior of subway stations. Hence, possible movements are restricted by physical obstacles. The space can be open in terms of entry and departure of nodes, or it can be closed and contain a fixed number of nodes at all times. The region of interest determines whether an open or closed system is most appropriate: if the stochastics of the population of nodes in the area cannot be neglected, then the model must be open. This is the case of regions that are too small to include the full whereabouts of the modeled nodes.

The mobility is constrained by node *capability*, *coupling* of nodes, and *authority* over nodes. Capability constraints refer to the limitations on human movement due to physical or biological factors, for example, the need to return to a given location after a journey (as for commuting), walking speed, access to cars or public transportation, and so on. Coupling constraints refer to the need to be in one particular place for a given length of time, often in interaction with other people. Constraints imposed by authority relate to the influence of control exerted on nodes to restrict their possible mobility, such as unsafe areas, work hours and shop opening hours, traffic rules, and other non-physical constraints. A structured space with constraints on mobility is referred to as *space-time geography* and it was first proposed by Hägerstrand in [39]. The author used the space-time path to demonstrate how human spatial activity is often governed by limitations, and not by independent decisions by spatially or temporally autonomous individuals.

To exemplify, consider synthetic mobility in form of random waypoint mobility [40]. It is characterized by mobility of a fixed number of nodes in a closed area with a convex boundary and without internal obstacles. The capability is given by the distribution of the speed of the flights the nodes make and the distribution of their pause times. There are not any coupling constraints since nodes do not have a physical size or any other form of interaction, and there is no authority constraining the movements other than the boundary.

In the real-world, the situation is substantially different. If we observe two nodes in light of this concept, direct communication between the nodes is possible when parts of their space-time paths overlap. Figure 5.1 illustrates this idea, showing the space-time paths for nodes A and B. Projection of a path on the space plane corresponds to the actual physical path that the node walks (or travels by car).

In addition to constraints on mobility, there are levels of abstraction. Human mobility can be seen as consisting of three levels [23]: At the *strategic* level humans

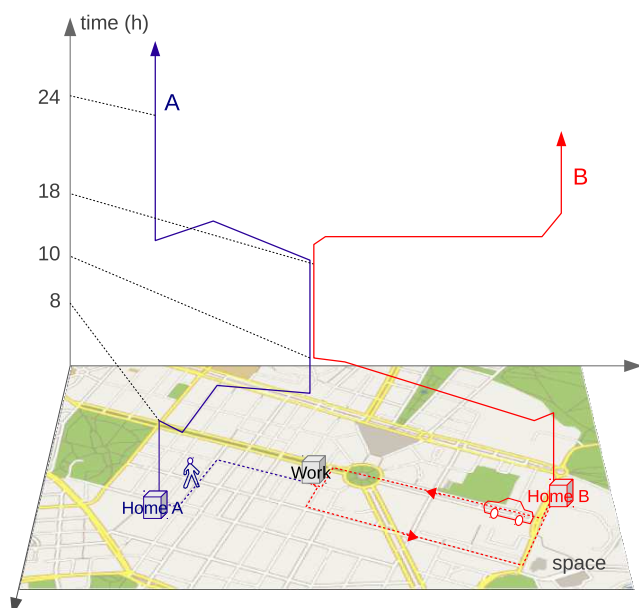


Figure 5.1: Contact opportunity for two nodes meeting at their common location of work.

decide on the activities they would like to perform and when to depart for an activity which leads to their daily movements, such as going to work, shopping, or taking a walk in the park. The *tactical* level considers the implementation of a strategic decision, such as choosing a way of travel, taking into consideration which is the shortest or fastest path as given by environmental factors like obstacles and congestion. At the *operational* level, the physical process of human movement is considered, including walking or driving speed, physical size of nodes or interaction with other traffic due to queuing for avoiding collisions. Returning to the RWP example, we see that the strategic level is the selection of waypoints and pause times (i.e. time between activities); the tactical level is the linear movement from a current location to the selected waypoint, and the operational level is the speed of flight. In Table 5.1, we exemplify the constraints on mobility for the three abstraction levels.

The spatial extent of a model affects the abstraction. It might be hard to discern the strategic from the tactical levels for a node that traverses a modeled region of interest and has its start and end locations outside the region: both levels influence the inflow of nodes at different points at the perimeter of the region. If we shrink the area, there will eventually not be any room for tactical decisions (i.e., when no

	Capability	Coupling	Authority
Strategic	Available time	Work locations areas for shopping	Regulated work hours shopping hours
Tactical	Means of transport	Schedules of public transport	Unsafe areas
Operational	Speed of walking or driving	Queueing and crowding	Speed limits traffic rules

Table 5.1: Examples of constraints on mobility at different levels of abstraction.

branching of movements is longer possible) and hence no need to separate the two levels; the main level is then operational. If start and end locations of a journey are the only points where communication occurs, then the tactical and operational levels together determine the time between communication opportunities and might not need to be separated, and the operational level might not need to be considered at all.

To summarize, a mobility model must have a determined region of interest. It can be open, allowing nodes to arrive into and to depart from the modeled region, or it might be closed and populated by a fixed number of nodes. The model also needs to capture the physical structure of the space and the mobility constraints of the nodes. Finally, it may represent how nodes take strategic decisions to make trips, and the tactical and operational level decisions to carry out the trips.

5.3 From structure to metrics

There are two random processes given by mobility that underlie opportunistic communication: the opportunity for contacts among (any) nodes, and the opportunity for meetings between specific nodes. The model for a specific scenario should capture these three random entities: inter-contact time, duration of contact, and type of meeting. The meeting types correspond to the different communication modes, and can be: unicast, if the forwarding of a message is from a specific node to another specific node, or multicast if it instead may reach a set of destinations. Hence a string of meetings has eventually to lead from the originator to the intended recipient (or recipients). The difficulty lies in deciding which intermediate meetings should be used to forward the message so that it progresses towards the destination. Uncertainty about a meeting, whether it is being conducive to the communication, is hedged by replicating the message, thus leading to a higher traffic load. A useful meeting in a content-centric mode of communication is with any node that can provide the sought-for contents or services. It then suffices to model the availability of contents and services, irrespective of which nodes provide them.

The performance of opportunistic communication systems is influenced by strategic, tactical and operational levels of mobility and the influence depends on the mode of communication. The coupling constraints affect decisions taken by a node at the strategic and tactical levels and introduces regularity in movement patterns which in turn affect the inter-meeting time among specific nodes. Some routing pro-

protocols for delay-tolerant networks try to take advantage of such non-randomness in node mobility to efficiently route messages to a given destination node [37, 41]. Mobility at the operational level affects node connectivity and the duration of individual contacts. This determines the amount of data that can be transferred over each contact [29].

5.4 Model analysis with respect to structure

To this end, there is a large body of work studying mobility and myriads of proposed mobility models. We choose three classes of models and show how they can be layered according to the three-level mobility structure.

Models based on statistical properties of mobility traces

The availability of advanced measurement techniques through pervasive technologies and services, has enabled researchers to obtain large collections of mobility traces and exploit statistical properties of mobility in order to refine existing models. Analysed traces span over various scales, both spatial and temporal, comprising datasets from GPS and cellular network positioning traces, to recordings of mobile devices associating with wireless access points, to *check-in* locations of users of the popular location-based social network Foursquare [42]. Reference [43] presents a comprehensive study of trajectory of 100,000 anonymized mobile phone users whose position was tracked for a period of six months. The authors have found significant regularity in human mobility, reporting the following main features:

- 1) Distances between two successively visited locations and pause times spent at locations follow truncated power-law distributions.
- 2) People tend to visit few popular locations and swarm near to those locations; the popularity of locations is proportional to the number of visited points inside swarms. We will refer to this feature as a *fractal* nature of visited locations.
- 3) Humans show the tendency to roam inside mobility areas bounded by their capabilities.

These findings corroborate Hägerstrand's observations and provide an analytic framework to describe human mobility patterns.

The first of synthetic mobility models to incorporate all the aforementioned statistical properties of mobility was *Self-similar Least Action Walk* (SLAW) model [24]. The model produces realistic human mobility patterns by generating fractal waypoints with power-law distributed distances between them. Next, the model applies the least action principle to decide, given the set of locations to visit, the order in which a person visits those locations. Least action principle aims to minimize the discomfort of a node (*walker*); in this case, the discomfort is the total distance of travel and coupled with this metric, the total journey time. When visiting a

location, a walker will strive to visit all the nearby locations first and travel to the distant ones later, unless there is a higher priority event in a remote location, such as an appointment.

Reflecting the three-level structure of mobility, we recognize that SLAW models the strategic and tactical levels of mobility. On the strategic level, the choice of activities an agent performs is given by the set of locations he chooses to visit during the day. In his daily travel, each walker visits a fixed set of locations, which corresponds to performing usual daily activities such as: going to work or school, going shopping after work hours, visiting various sites (e.g. classrooms, library) on a university campus. Then, to add some randomness to his travel, a walker chooses a set of additional locations he will visit that day; this set is chosen at random and changes on a daily bases. This randomness accounts for the occurrence of sporadic events which would influence walkers to leave their usual roaming areas, potentially travelling long distances: meeting friends and family living in another part of the city, or exploring new places to dine out are just some examples.

Pause times at locations are drawn from a truncated power-law distribution and the average value is adjusted so that the whole trip ends within a fixed time period. Given both the time constraint and the activity agenda, a walker plans his trip by deciding on the order of activities to perform and the time devoted to each (pause time). These choices are made on the tactical level, as well as the choice of the path between two destinations (a straight line). On the operational level the model considers only the speed of movement, which for the sake of simplicity is set to be 1 m/s.

By incorporating dominant statistical features of human mobility, SLAW is able to produce realistic individual walking paths. This, however, comes at the cost of computational complexity due to generation of fractal waypoints. What the model misses to capture (and what could be of more importance for a certain type of applications) is the social structure and its underlying mechanisms that drive mobility. The random choice of visited places does not reflect real-life situations of people planning their trips and travelling *to meet* their friends or colleagues, or attend appointments. Therefore, with respect to the constraints on mobility, this model considers, to some extent, node capability and authority constraints, but it ignores the coupling constrains.

In the following subsection we discuss about models that take social interactions among nodes as a starting point to explore mobility.

Social-based mobility models

The most recent approach in modeling mobility is based on complex social network theory. Models in this class consider human relations between nodes as a driving force for mobility, governed by the intuition that a node's movement is highly influenced by the behaviour of other nodes with whom he shares social ties. In other words, if two nodes are connected by some social bond, choice of destination of one node, as well as the time to visit it, may influence the movement of the

other, depending on the strength of that bond. This idea aligns with our notion of coupling between nodes.

Pioneering works in this field were *Community-based Mobility Model* (CMM) [27], a model purely based on social graph connections, and its extension, *Home-cell Community based Mobility Model* (HCMM) [28], which added location-driven mobility.

HCMM aims to join social and spatial aspects of mobility by including attractions to locations in which social activities take place. The operation starts by separating nodes into communities, and assigning each community to its home location (a cell of the grid). Nodes then start moving either inside their own cell, or towards other cells, to which they are attracted according to the popularity of that cell among their friends.

The choice of the destinations fits with the strategic level choice and the set of visited locations is determined by social relations. With respect to the tactical and operational level decisions, this model exhibits a degree of abstraction similar to that of RWP: linear movement towards the next destination and uniform speed with a notable difference that HCMM captures truncated-power law distributed trip lengths, which is a good fit to the trace analysis mentioned earlier. As opposed to SLAW, HCMM is tailored to capture the coupling constraints of mobility, by bringing together nodes from the same community.

This basic concept of social-driven mobility has been widely adopted and further developed to include additional properties, e.g., membership in different communities modeled with time-varying social graphs [44].

Lastly, we describe models that consider mobility at a lower level of abstraction than the models of the previous two classes.

Modeling daily patterns

Models in this class aim to reproduce realistic movement by utilizing predictive patterns in human daily activities. In [45], Ekman et al. describe the *Working Day Movement Model* which, as the name suggests, combines several main activities an average person performs on a daily basis. People travel to work in the morning, spend a significant amount of time at work and finally return to their home or meet friends in the evening. First, note that the order of these activities corresponds to the strategic level decisions. Daily activities are modeled by different submodels: home, office, transport and evening model, which significantly differ in the level of abstraction. For example, the home model simply generates long inactive periods at home locations; the office movement assumes low mobility inside the office (and the building), while the transport model allows choice of different means of transportation: a person can walk to his destination, move by car, or take the bus. The choice of transportation is made on the tactical level, and the speed at which a person moves, either by walking or driving, is on the operational level. Thus, we conclude that this approach achieves to capture, to some extent, all levels of mobility, but the disadvantage is that it requires laborious configuration of a set of input

parameters, e.g. home and office locations, routes and bus schedules.

Another example in this class is the *Agenda Driven Mobility Model* proposed in [46], where the authors explore the data from the National Household Travel Survey of the U.S. Department of Transportation to extract realistic distributions of activities and dwell times. This model encompasses a large set of possible daily activities, and detailed geographic maps with constrained topology, thus giving extremely thorough representation of human mobility. With respect to the three-level structure of mobility, this model presents the most comprehensive approach including all layers from the strategical (users can choose among around 30 different activities) to tactical (choice of streets and paths) to operational (speed). While aiming to be very comprehensive, this model suffers from high complexity and since it heavily relies on statistical analysis of a specific scenario, it is questionable whether it can be deployed in other scenarios.

Finally, let us emphasize that a majority of models focuses on the tactical and strategic levels. Mobility on the operational level has rarely been studied; yet, it is the physical process of movement and interaction between nodes (and obstacles) that determine whether a contact opportunity will result in successful message forwarding. Some initial studies, such as [29, 30] where the authors studied path durations, indicate that physical characteristics of the human mobility have less significant impact than the actual scenario in hand.

Finding a solution to model all aspects of mobility, while trading between complexity of the model and its applicability in various scenarios is quite a challenge. Therefore, the choice of the appropriate mobility model is essential. In the next section, we return to the use cases described in chapter 3, and highlight what are the case-specific aspects that the model should capture.

5.5 Mapping mobility models to scenarios

We focus our attention on three previously proposed use-cases: distributed vehicular data sensing, opportunistic social networks and opportunistic services in developing/rural regions. These applications conveniently illustrate how different the requirements imposed on mobility modeling are.

In the vehicular data sensing application, communication takes place in an urban area. Movement inside the area is defined by road maps and regulated by traffic regulations such as speed limit, mandatory direction, and traffic lights. Since the start and end locations are likely to be outside of the area, the model needs to consider only the tactical and the operational level and describe the paths and speeds for the vehicular movement. Further, the model should represent stochastics of an *open* system, characterized by arrival and departure processes, which may fluctuate over different parts of the day and week. A similar level of abstraction can be applied to models for opportunistic services in urban regions, assuming pedestrian movement instead of vehicular.

A model appropriate for opportunistic social networking may not necessitate

detailed analysis on the operational level, but it certainly needs the knowledge of human social patterns: whom they meet, where and how often, which are described on the strategic level.

Opportunistic services in developing/rural regions are particularly interesting from the modeling perspective. Depending on the target scenario, the model might need to capture very heterogeneous mobility, from pedestrian to bicycle and vehicular movement. Mobility in this case is mainly constrained by node capabilities that relate to the tactical level (nodes' means of transport) and the operation level (speed of walking or driving), as well as coupling effects (schedules of public transport).

5.6 Conclusion

In this chapter, we introduced a three-level structure of mobility, consisting of the strategic, tactical and operational levels, and we showed how movements are often governed by different limitations. We examined three classes of mobility models in the light of this approach, showing that a single model is unable to capture all characteristics.

We conclude that the strength of an (analytic) model is mainly in its analytical tractability and the ability to mirror scenario-specific features of mobility. This inspires our approach to studying mobility and in the next chapter we propose a novel approach to model a particular phenomenon, focusing on open-system dynamics rather than on individual node movement.

6 *A queueing mobility model*

In this chapter we propose an analytic queueing model for content dissemination. We denote the model as *meeting-point* mobility model, which should suggest that the area represents a point of interest visited by many nodes. The model focuses on queuing effects of mobility; as a first approximation, we will neglect detailed individual mobility patterns and assume that nodes inside the area are always connected regardless of their movement. Thus, the internal mobility does not affect connectivity. We will revisit this assumption in section 6.1 and investigate the impact of the operational-level mobility. First, we describe the model in detail and then we introduce the performance metric we use to evaluate performance of content dissemination.

6.1 Description and analysis

We consider an open system consisting of mobile nodes equipped with short range radios, such as WiFi or Bluetooth, and ample data storage. The mobile nodes arrive to the meeting point according to some arrival process, reside there for a particular amount of time and eventually leave (depart the system). We assume the same transmission range Δ for all nodes and the size of the meeting point area to be sufficiently small in comparison to Δ : whenever two nodes collocate inside, they will be in communication range of each other and able to exchange data.

Some of the nodes entering the area carry contents and transfer them to others when contact is established. We are interested in analyzing the achievable content spreading. For the sake of simplicity, we assume that all nodes in the area are interested in obtaining the same data element. Thus, every contact opportunity results in data exchange; the content spreading scheme is epidemic. Denote by λ the arrival rate of the nodes and by $p \in [0, 1]$ the proportion of nodes that carry the content (in the text, we will also use the term *injection probability* for p). Further, the size of the data item is small in comparison to the data link capacity and the transfer time is hence negligible.

Assuming that arrivals occur according to a Poisson process and that the node sojourn time (t_s) is exponentially distributed with mean value $\bar{t}_s = 1/\mu$, we can model the system with the Markov chain depicted in Figure 6.1 (a).

The states of the chain are $S_{i,j}$ where $j, j \geq 0$, denotes the number of nodes in the area and $i \in \{0, 1\}$ the presence of the contents inside: in states $S_{1,j}$ for

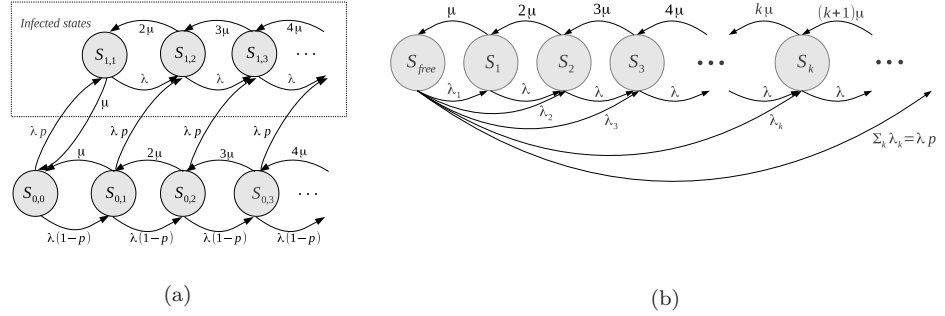


Figure 6.1: Markov chains for the meeting-point mobility model.

$j \geq 1$ all the nodes in the area have the content. In state $S_{0,0}$ the system is empty. When the system is in the lower branch of the chain, i.e. in any of the states $S_{0,j}$, it transits to state $S_{1,j+1}$ with the rate λp , with the arrival of a node that carries the contents. Otherwise, the system transits to state $S_{0,j+1}$ with the rate $\lambda(1-p)$ or to state $S_{0,j-1}$ when a departure occurs. The system transits from state $S_{1,j}$ to state $S_{1,j+1}$ with the rate λ or to state $S_{1,j-1}$ with the rate $j\mu$. Borrowing the terms from epidemic modeling, we can categorize states $S_{1,j}$, $j \geq 1$ as *infected* with contents and nodes that do not carry the contents we call *susceptible*. An arriving node obtains the contents if it finds the system in any of the infected states. Once the contents enter the system, it will reside inside as long as the system remains non-empty.

Alternatively, the epidemic process can be described with the Markov chain in Figure 6.1 (b), with all the uninfected states collapsed into a single state. The states of this chain are:

- S_{free} : the system is free of contents, independent of the number of nodes inside,
- S_k : k nodes are in the area and they all possess the contents.

Consider the state S_{free} : when a node arrives with the contents, all the nodes in the area will obtain the contents in infinitesimally short time upon arrival (by broadcast). The system transits to state S_k with probability P_k , where k is the total number of nodes including the last one arrived. The time that the system spends in the free state is exponentially distributed random variable with parameter λp . Given that the chain is in the free state, nodes without the contents arrive according to a Poisson process with rate $\lambda_0 = (1-p)\lambda$, but also leave with rate μ . Then, P_k is given by $P_k = P\{N(t) = k-1\}$, where $(N(t), t \geq 0)$ is the size of an $M/M/\infty$ queue of nodes not carrying the contents.

Lemma: Given that the system is in state S_{free} , the probability P_k that the system transits to S_k with a new arrival is

$$P_k = \int_0^\infty \lambda p \frac{((1-p)\lambda(1-e^{-\mu t}))^{k-1}}{\mu^{k-1}(k-1)!} e^{-\frac{(1-p)\lambda(1-e^{-\mu t})}{\mu}} \cdot e^{-\lambda p t} dt \quad (6.1)$$

Proof: Denote by $X(t)$ the number of arrivals in S_{free} until time t (observed since time 0, when the system got empty). Assuming that i nodes arrived by the time t and n of them are still present at that time,

$$Pr\{N(t) = n\} = \sum_{i=n}^{\infty} Pr\{N(t) = n | X(t) = i\} \frac{e^{-\lambda_0 t} (\lambda_0 t)^i}{i!} \quad (6.2)$$

The probability that a node that arrived in the interval $(x, x + dx)$, $dx \rightarrow 0$ will still be present at time t is $e^{-\mu(t-x)}$. Hence, the probability that an arbitrary arrival is still in service at time t is

$$q_t = \int_0^t Pr\{\text{sojourn time} > t - x \mid \text{node arrived in } (x, x + dx)\} \cdot Pr\{\text{node arrived in } (x, x + dx)\} dx \quad (6.3)$$

Since the arrivals are Poisson, $Pr\{\text{node arrived in } (x, x + dx)\} = \frac{dx}{t}$ and we have

$$q_t = \frac{1}{t} \int_0^t e^{-\mu(t-x)} dx = \frac{1 - e^{-\mu t}}{\mu t} \quad (6.4)$$

The probability q_t is independent of any other arrival. Next,

$$Pr\{N(t) = n | X(t) = i\} = \binom{i}{n} q_t^n (1 - q_t)^{i-n}, \quad n \geq 0. \quad (6.5)$$

The distribution of the transient probability is given by

$$\begin{aligned} Pr\{N(t) = n\} &= \sum_{i=n}^{\infty} \binom{i}{n} \frac{q_t^n (1 - q_t)^{i-n} e^{-\lambda_0 t} (\lambda_0 t)^i}{i!} \\ &= \frac{(\lambda_0 q_t t)^n e^{-\lambda_0 q_t t}}{n!}, \end{aligned} \quad (6.6)$$

which is a non-homogeneous Poisson with mean $\lambda_0 q_t t$. Denote by f_{free} the distribution of the time that the system spends in the free state. Since this time is the sum of geometric number of exponential random variables, it is again exponentially distributed and we have $f_{free}(t) = \lambda p e^{-\lambda p t}$, $t > 0$.

Finally, we obtain the transition probabilities:

$$\begin{aligned} P_k &= \int_0^\infty Pr\{N(t) = k - 1\} f_{free}(t) dt = \\ &= \int_0^\infty \lambda p \frac{((1-p)\lambda(1-e^{-\mu t}))^{k-1}}{\mu^{k-1}(k-1)!} e^{-\frac{(1-p)\lambda(1-e^{-\mu t})}{\mu}} \cdot e^{-\lambda p t} dt. \end{aligned} \quad (6.7)$$

We have defined the Markov chain to depict the process of epidemic content dissemination. The metric we introduce is the *content distribution probability*, denoted by P_{cd} , and representing the proportion of nodes carrying the data upon their departure from the system.

Computation of content distribution probability

The total population of nodes holding the contents when they leave the system comprises the carrier nodes and the nodes that become *infected* during their stay inside the area. An uninfected node obtains the contents in two cases: 1) arriving to the system when the system is in any of the infected states, and 2) if it finds the system in state S_{free} and an arrival of contents occurs before the observed node departs. In order to find this probability, we need to find the state probability π_{free} . The local balance equations for infected states are:

$$(k+1)\mu\pi_{k+1} = \lambda\pi_k + \lambda p \left[1 - \sum_{j=1}^k P_j \right] \pi_{free} \quad (6.8)$$

The following complete the system of equations:

$$\begin{aligned} \lambda p \pi_{free} &= \mu \pi_1 \\ \pi_{free} + \sum_{k=1}^{\infty} \pi_k &= 1 \end{aligned} \quad (6.9)$$

Denote by $\rho = \frac{\lambda}{\mu}$ the occupancy of the system. Finding the probability that the system is in the *free* state at an arbitrary point of time is sufficient for the calculation of P_{cd} . Substituting probabilities P_k given by (6.7) in (6.8) does not lead to a closed-form solution of the system of equations, thus we use numerical methods to obtain π_{free} .

Let us find the probability that a departing node carries the contents. This event can be partitioned into three sub-events:

1. *Event A*: a node already carries the contents when it enters,
2. *Event B*: a node obtains the content when it arrives in any of the infected states,
3. *Event C*: a node arrives when the system is in the free state but obtains the content before departing.

Probability of the event *A* is simply $P\{\text{event } A\} = p$, probability of the event *B* equals $P\{\text{event } B\} = (1 - \pi_{free})$; let P_C denote the probability of event *C*. The content distribution probability is then

$$P_{cd} = 1 - (1 - P_A) \cdot (1 - P_B) \cdot (1 - P_C). \quad (6.10)$$

Given that a node arrives in state S_{free} , with probability $1 - P_C$ it does not obtain the contents. The arrival process of contents is Poisson with the rate λp , and the time a node remains in the system is exponential with the rate μ . Then

$$1 - P_C = \int_0^\infty e^{-\lambda p t} \cdot \mu e^{-\mu t} dt = \frac{1}{1 + \rho p} \quad (6.11)$$

and finally, from (6.10), (6.11) we get:

$$P_{cd} = 1 - \frac{(1-p)\pi_{free}}{1 + \rho p} \quad (6.12)$$

Expression (6.7) gives an exact result for probabilities P_k ; however, for easier computation of the chain's stationary distribution and π_{free} , we introduce a convenient approximation. Let $P_k \approx p(1-p)^{k-1}$, $k \geq 1$. Then, we get from (6.8) the system of local balance equations:

$$(k+1)\mu\pi_{k+1} = \lambda\pi_k + \lambda p(1-p)^k \pi_{free} \quad (6.13)$$

which gives the state probability

$$\pi_{free} = \frac{e^{-\rho}}{1 - \rho(1-p)I(\rho, p)} \quad (6.14)$$

where $I(\rho, p) = \int_0^1 \frac{1-x}{1-x(1-p)} e^{-\rho x} dx$, and the approximation for the probability of content distribution

$$P_{cd} \approx 1 - \frac{e^{-\rho}(1-p)}{[1 - \rho(1-p)I(\rho, p)](1 + \rho p)} \quad (6.15)$$

To validate the analytic results, we compare those to the results obtained from MATLAB simulations (Figure 6.2). The plots show estimated probability P_{cd} with 95% confidence. The number of nodes in each trial was 10^5 . Figure 6.2 validates our analytical results and also shows a good match between the exact solution in Equation 6.12 and the approximation for P_{cd} in Equation 6.15.

Sensitivity of the model

Let us further explore how sensitive the meeting-point model is to different input parameters: injection probability, queue length, sojourn time distribution and the arrival process of nodes. We can observe from Figure 6.2 that for the same system load, the probability P_{cd} rapidly increases with probability p .

Notably, the impact of queue length is also significant. For example, with very low probability of content arrivals $p = 0.5\%$, probability P_{cd} yields 53.8%, 72.6% and 87% for 5, 6 and 7 nodes in the system, respectively. We see that the content distribution performs well even in cases with rare content arrivals, given that the

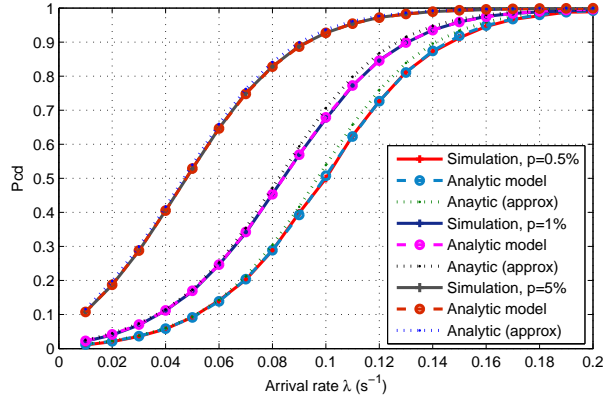


Figure 6.2: Probability of content distribution for various injection probabilities p and mean sojourn time $t_s = 50$ seconds.

number of nodes in the system is sufficient. For low p , P_{cd} values are close to the proportion of time the system is infected. Thus, we infer that the model encompasses a *virtual storage* effect (also called *floating content* in [47]): the contents remain in the system despite absence of a storage node, e.g. an access point. Intuitively, this is an obvious consequence of nodes queuing and the *all-peers-in-range* connectivity in the system.

Now, we relax the assumptions on the sojourn time distribution to evaluate its impact on content distribution. Plots in Figure 6.3 (a) show the content distribution for the following sojourn time distributions: exponential, three uniform distributions and a Pareto distribution. The mean value for all distributions is 50 seconds. Uniform distributions have support on intervals: [10, 90], [30, 70] and [40, 60] seconds and the Pareto distribution has minimum value 30 seconds and shape parameter $\alpha = 2.5$. The injection probabilities p for the two sets of curves are 1% and 5%. The difference in performance is not significant; the exponential distribution achieves the highest performance, followed by Pareto and uniform distribution. The reason for these discrepancies is the difference in residual time during which a node can still obtain the content if it arrives before its departure. However, this finding can be used to simplify the modeling of departure process and assume the inter-departure time is exponentially distributed.

Contrary to the node sojourn time distribution, the arrival process affects content distribution much more, as the curves in Figure 6.3 (b) show. The mean arrival rate λ is the same for all the processes: a Poisson process, an Erlang arrival process consisting of four stages, each with the rate $\lambda/4$, and a two-stage hyper-exponential process with parameters 0.35λ and 5.7λ for the rates, and 0.31 and 0.69 selection probabilities for the first and the second phase, respectively. The coefficient of

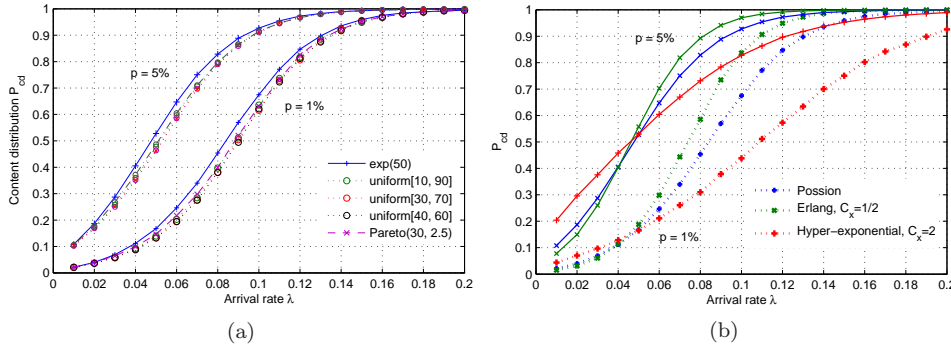


Figure 6.3: Content distribution as a function of arrival rate and node sojourn time distribution (a), and arrival process (b).

variation for the Erlang distribution is $1/2$ and it is 2 for the hyper-exponential distribution. We look into two sets of curves for P_{cd} : for the lower sets, probability $p = 1\%$ and for the higher sets $p = 5\%$. When $p = 1\%$, the burstiness of the hyper-exponential arrivals has a negative effect on the distribution since many arrivals occur in a short time, but the proportion of content-carriers is low.

Discussion on all-peers-in-range connectivity assumption

Previous analysis allowed us to study the achievable performance of an epidemic scheme. However, we recognize that the assumption of *perfect infection*, that is, the assumption that the infection occurs whenever susceptible nodes are co-located with infected nodes, is too optimistic. As we will see, even in small areas for which dimensions are comparable to the transmission range, internal mobility is likely to affect the infection process; also, the temporal overlap of nodes might be too short to transfer the contents. Therefore, we relax this assumption and model the case of non-perfect epidemics. Denote by β the pairwise infection parameter; it is the rate at which previously uninfected nodes get infected due to internal mobility. This parameter relates to mobility and for different scenarios it can be extracted either by simulations or trace analysis. Then, this type of epidemic process can be represented by the two-dimensional Markov chain in Figure 6.4. States of the chain $S_{i,j}$ denote the number of infected nodes, i , and the total number of nodes inside the area, j .

Despite the regular structure this chain seems to own, the chain does not easily lend itself to closed-form solution and solving it would call for numerical methods. Thus, rather than finding the state probabilities and calculating the probability of content distribution based on those probabilities, similarly to the previous case, we simplify the analysis and study non-perfect epidemics by means of simulation.

The setup is similar to the one with the original model where nodes arrive to an area according to a Poisson process and their sojourn times are exponentially

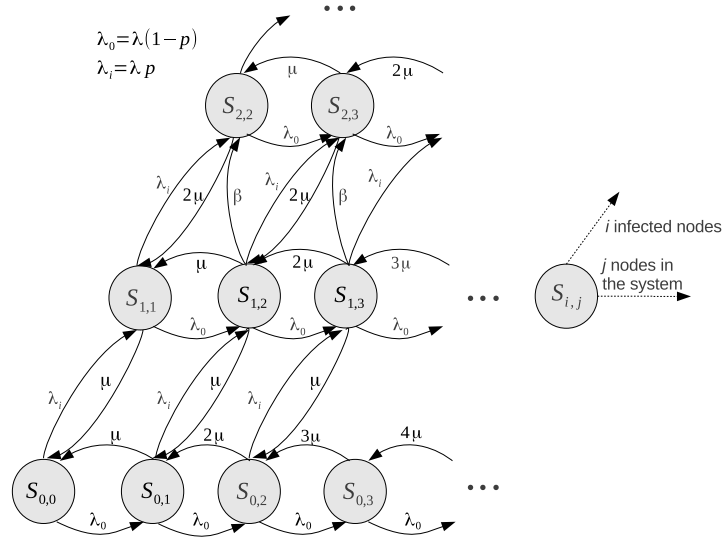


Figure 6.4: The Markov chain for non-perfect epidemics.

distributed, except that now we introduce internal mobility in the simulations. The simulation area is square-shaped with a length denoted by L . Node movement corresponds to random-waypoint mobility model with the speed between 0.5 and 1.5 m/s and pause time interval $[0, 1]$ second.

Figure 6.5 shows the content distribution probability (P'_{cd}) as a function of length L , average system occupancy, $\rho = \lambda/\mu$ and probability p which denotes the injection probability as earlier. We ran simulations with 2000 nodes and three values of injection probabilities $p = (1\%, 5\% \text{ and } 10\%)$. The simulation results were averaged over 100 simulation runs (representing 80% confidence intervals). The transmission range is $\Delta = 10$ m and the area dimensions vary from 10 m to 100 m. In Figure 6.5 (a) the arrival rate is $\lambda = 0.05 \text{ s}^{-1}$ and the average sojourn time $1/\mu = 100$ s, which gives occupancy of 5 nodes on average, while in the second case (Figure 6.5 (b)) the average occupancy is 10 nodes ($\lambda = 0.08 \text{ s}^{-1}$, $1/\mu = 125$ s). Clearly, the lower the number of nodes in the area, the less contact opportunities they will have and therefore, the content distribution probability decreases more rapidly. In the first case, we see that the simulation result decreases to 50% of the analytical value for $p = 1\%$ already for areas of size three times the transmission range. In the second scenario the decay is slightly slower with 13, 7, and 6% for $p = 1, 5$ and 10%, respectively and area length of four times the transmission range, after which the decrease can be approximated as a linear combination of negative exponentials. In notation,

$$P'_{cd}(x, \rho, p) = \alpha(x, \rho, p)P_{cd}(\rho, p) \quad (6.16)$$

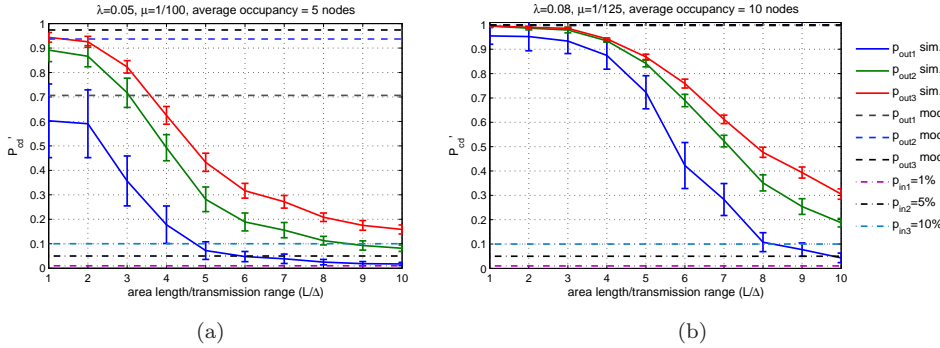


Figure 6.5: Probability of content distribution as a function of simulation area length, system occupancy and injection probability.

where $x = L/\Delta$, $P_{cd}(\rho, p)$ is given by (6.15) and $\alpha(x, \rho, p) = a(\rho, p)e^{-b(\rho, p)x}$. As an example, the curve which corresponds to $p = 1\%$, and $\rho = 5$ (in Figure 6.5 (a)) can be fitted to exponential function $\alpha(x, \rho, p) = ae^{bx}$, where $a = 2.9$, $b = 0.595$.

6.2 Model validation

In this section we examine two mobility scenarios, and show that real-life mobility traces support the assumptions used in the meeting-point model. We use two data sets, both representing pedestrian movements inside a building; while the environments where the traces were recorded are similar, the sets capture different node dynamics.

HOPE set

The set [48] contains positioning data, collected from the *Hackers On Planet Earth* (HOPE) conference held in July 2008 in New York. Conference attendees received RFID badges that could identify and track them uniquely across the conference space. Badges would send out beacons to RFID readers roughly every 30 seconds, locating the attendees in one of 21 zones on two floors of the conference hotel. The trace set contains records from 1280 participants during three conference days. We focus our attention on one of the floors which is characterized by higher mobility and choose the time window from 12:00 to 14:00 during the second day of the conference, when the highest number of the participants were active and traceable. This subset includes traces of 914 participants. Zones located on this floor were, for instance: a demonstration area, information desk, exhibition area, vendor and network operators stands; the other floor zones comprised mostly lecture rooms.

Figure 6.6 depicts the floor plan consisting of fifteen different zones; nodes were located in one of those areas when recorded by RFID readers located on the floor.

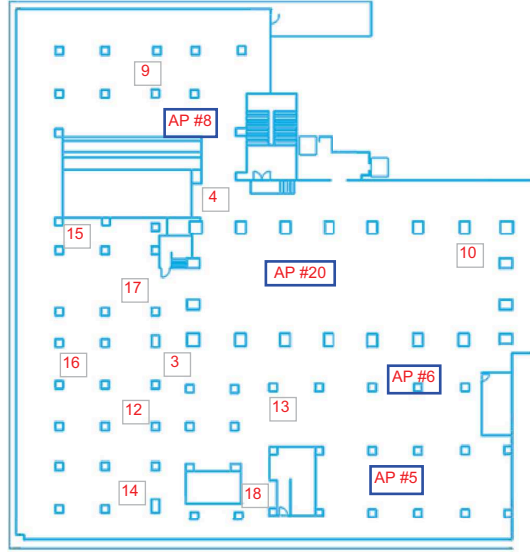


Figure 6.6: Floor plan with the positions of 15 RFID readers.

We choose the four most visited areas (5, 6, 8, 20) and show how these can be modeled with our model.

We estimated the probability mass function (PMF) for the number of arrivals and the queue lengths during a time slot of 30 seconds (the time between two consecutive timestamps). Figure 6.7 shows the corresponding PMFs for four areas. The empirical data is represented with red cross markers, while the solid lines represent Poisson distributions with mean values equal to those estimated from the traces. We observe that a Poisson distribution shows relatively good approximation to empirical PMFs. Next, the distributions of sojourn times show strong power-law decay with the mean values 128.8, 70.4, 60.9 and 51.1 s for areas 5, 6, 8 and 20, respectively. The average arrival rates to these areas are 0.12, 0.17, 0.31 and 0.18 s^{-1} .

Then, we estimated the values of sojourn time and arrival rates over shorter time windows (60 seconds) and used those values to compute the content dispersion in the observed areas. The curves in Figure 6.8 correspond to simulation and analytic results for two values of injection probability ($p = 0.1, 1\%$). Note that the analytic results fit the simulation results; but also, the curves for two different p are indistinguishable. This result stems from the setup where the arrival rate and node sojourn time, and subsequently, the number of nodes in the queue is sufficiently high, thus the content distribution probability is always close to 1.

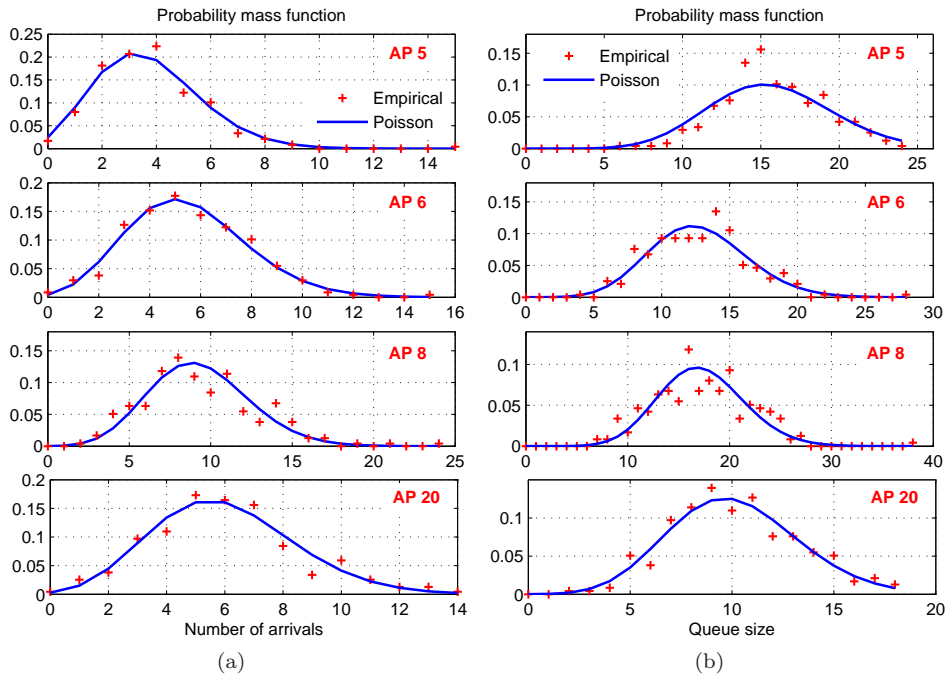


Figure 6.7: PMFs for number of arrivals (a), queue size (b) during 30 s time intervals (HOPE).

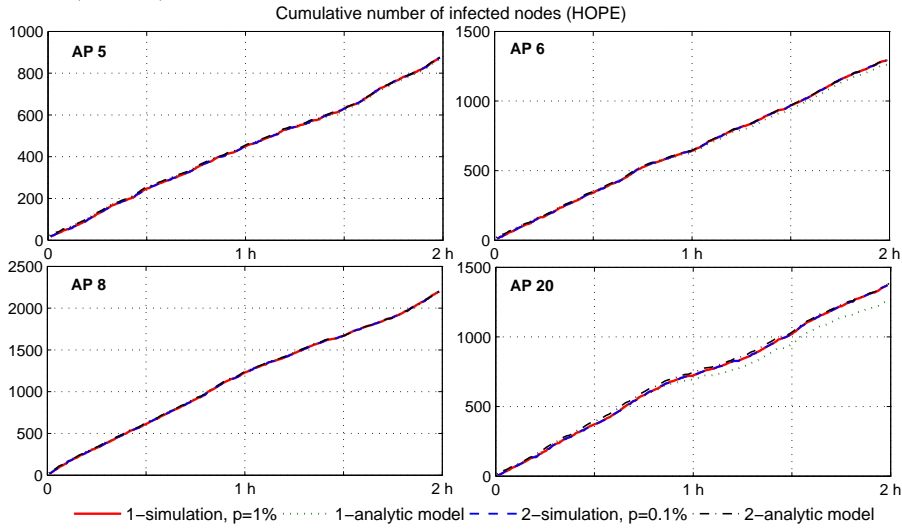


Figure 6.8: Cumulative number of nodes that obtained the contents (HOPE).

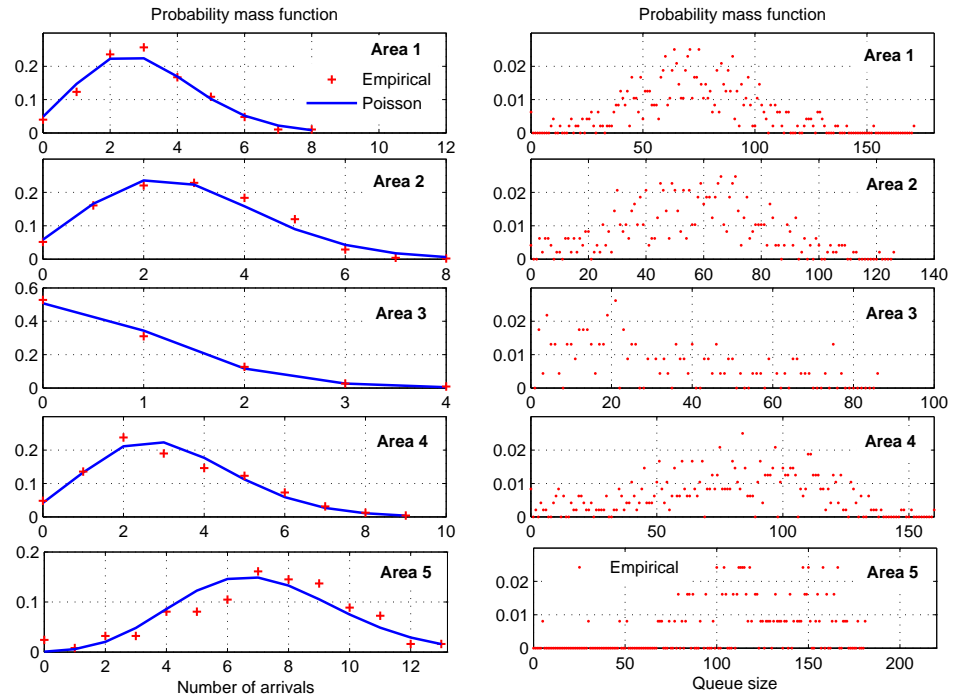


Figure 6.9: PMFs for number of arrivals (a), queue size (b) during 30 s time intervals (Humanet).

Tecnalia Humanet

The traces [49] describe human mobility and social behaviour of participants in an office scenario. The data collection campaign was carried out in a company building and contains the proximity traces and dynamics of 56 participants (employees) carrying Bluetooth equipped devices during one working day. For location purposes, 30 stationary nodes were distributed in strategic zones such as offices, corridors, cafeteria, meeting rooms, etc., all over the building. The minimum time granularity of the dataset is around 5 seconds. The traces contain information regarding the identity of the encountered nodes, the starting and ending times of the encounter, as well as the information regarding nodes' dynamics (whether the device was moving, standing still or left aside in horizontal position) and transmission power changes. From this set, we extracted the records containing encounters between nodes and stationary nodes, implicitly assuming the coverage area of that node to be a meeting-point area. Although the records do not reveal the location of stationary nodes (e.g. a node was positioned in the corridor or in an office), conclusions about some of those stationary nodes may be drawn from the starting time when encounters occurred and their durations. For example, records of long

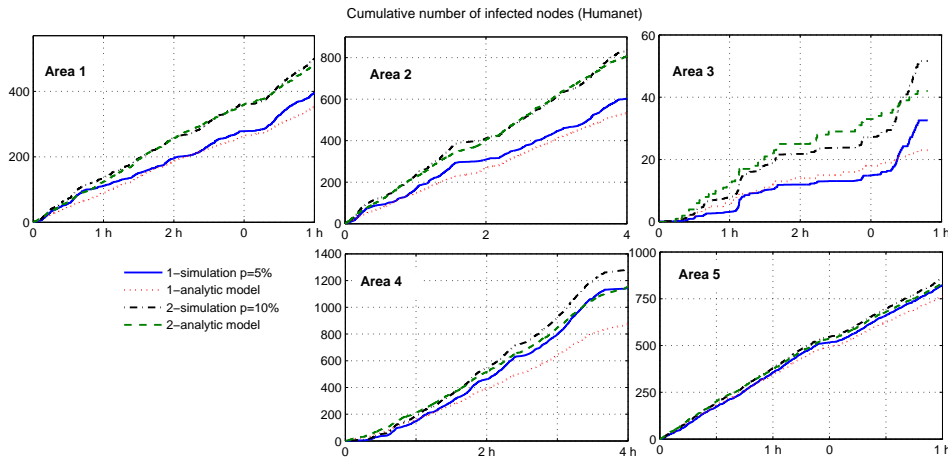


Figure 6.10: Cumulative number of nodes that obtained the contents (Humanet).

contacts would indicate that the nodes were positioned inside the offices or similar areas where the nodes remain for longer time. Next, a burst of contacts between one specific node and many nodes, all starting around 14:00, may lead to a conclusion that the node was located in the cafeteria or a similar common area. With respect to open-system dynamics, we recognized five (coverage) areas to resemble our model.

Similarly to the analysis of the previous traces, we chose time intervals when the highest activity of nodes were measured, with duration of 2, 4, 2, 4 and 1 hour respectively. The estimated average arrival rates are 0.1, 0.09, 0.02, 0.1 and 0.2 s^{-1} and the mean sojourn times 24, 20, 32, 25 and 17 s. Note that nodes returning to an area are considered as new arrivals. While the arrivals seem to follow Poisson distribution (we observed that the inter-arrival times have exponential distribution), the sojourn time distributions for these areas do not follow exponential distribution, and thus it differs from our model. The sojourn-time distribution seem to be heavy tailed, which is also confirmed by results depicted in Figure 6.10. For probabilities $p = 5\%, 10\%$ we estimated the numbers of nodes that get infected over time. It can be seen that the analytic results underestimate the performance of content distribution in comparable cases, which may be due to infection by nodes who stay in the area for very long times.

6.3 Applications

In the previous sections we described and analysed an analytic model to capture pedestrian mobility and epidemic spreading of contents in small areas. Now, we show how this rather simple model can be integrated into more complex models.

We propose using meeting point models as building blocks to build a queueing network, and in the parlance of queueing theory, we will refer to blocks as *stations*. Each station can be completely described by a set of input parameters: inflows of nodes and contents (given by the arrival rate and injection probability), and sojourn time distributions. Note that section 6.1 describes how to apply scaling laws when modeling larger areas, intrinsically similar to meeting points, but inside which the internal mobility cannot be neglected.

A four-station queuing network

First, we studied the behaviour of a queueing network consisting of four stations, and nodes were restricted to unidirectional movement in the network. In order to obtain the first insights, we use the HOPE trace and focus on the areas previously described in section 6.2. We model the whole building floor as a network of four meeting point models and investigate how the content would spread in such a network. To simplify the analysis, we introduce the following assumptions: 1) we disregard content distribution in the other floor areas and 2) assume that nodes' paths through the network are unidirectional, that is, a node cannot return to previously visited area (station). The performance metric we analyse here is again the probability that a node contains the content, but now upon its departure from the network. Figure 6.11 (a) shows example paths between stations 8 and 5. Content spreading works as follows: content is introduced in one of the stations (8 or 5) and the nodes departing from the area carry the contents with probability p . Then, nodes visit other stations or depart from the entire network. We assume two stations to be the starting points and established several (not all the possible) routes through the network. The transition probabilities between the areas, as well as the arrival rates and average sojourn times are taken from the previous analysis and used to compute probabilities of content distribution at each of the four stations. Figure 6.11 (b) shows the average probability of content distribution p_{avg} as a function of injection probability p . Noticeably, p_{avg} for the routes starting at the same station varies on order of 1%, while the differences in spreading on the routes starting from different stations is more prominent for lower p . For example, when 5% of nodes carry the contents initially, spreading is more efficient on the routes starting from station 5 than on the routes starting from station 8, with differences of around 20% of infected nodes.

This finding leads to a conclusion that the performance of content spreading depends on the routing through a network of queues and calls for more investigation of the network properties for specific scenarios. It can be of significant use for designing purposes; for example, deciding on the locations of access points that would distribute the content. Knowing the exact topology of the area and mobility characteristics, the optimal solution can be engineered by relatively little computing efforts. However, we do not delve into further analysis here, but address another important property of the composite network model.

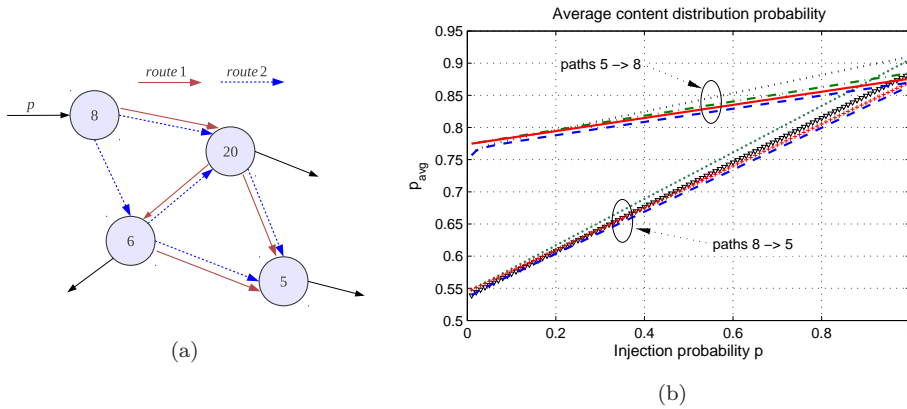


Figure 6.11: Example of unidirectional paths in the HOPE scenario (a). Average probability of content distribution in a four-station network (b).

A two-station cyclic queuing network

In the previous section we assumed that nodes traverse the network following unidirectional paths. This restricted type of movement can be found suitable for some scenarios when, due to regulations, pedestrians have to follow certain paths. In many other scenarios it can be found less realistic; for example pedestrians strolling in a shopping mall are likely to return to places previously visited.

Therefore, we extend the model of our queuing network and allow cyclic movements. To deal with this problem mathematically, we will restrict our attention to a two-station network depicted in Figure 6.12. Nodes enter either of the two stations, with arrival rates λ_i , and upon the service completion, transit to the other station with probability q_{ij} or leave the network with probability q_{i0} , where $i, j \in \{1, 2\}$. The sojourn times are exponentially distributed with average $1/\mu_i$. Initially, content is injected with probability p only to station 1, but as the content carriers visit station 2, spreading will occur in both stations. Then, departures from station 2 will feed station 1 with more carriers and eventually, the spreading process gets amplified throughout the network.

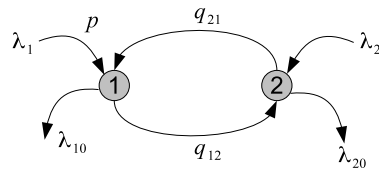


Figure 6.12: A queuing network consisting of two meeting-point stations.

At this point, recall that our model assumes that the contents arrive according to a thinned Poisson process. In case of a two-station network, this assumption does not hold in general: departures of infected nodes from one station are no longer independent. However, depending on the routing probabilities q_{ij} , and the departure rate of contents, certain approximations can be introduced, assuming that the contents arrivals are Poisson.

The network can be described with the set of equations:

$$p_1 = P_{cd}(\rho_1, p + p_2) \quad (6.17)$$

$$p_2 = P_{cd}(\rho_2, p_1) \quad (6.18)$$

where function $P_{cd} = P_{cd}(\rho, p)$ is given by (6.15).

Table 6.1: The two-station network parameters.

Set	1	2	3
λ_1	0.01	0.01	0.012
λ_2	0.012	0.01	0.01
$\mu_{1/2}$	0.02	0.02	0.02
q_{12}	0.5	0.5	0.4
q_{21}	0.4	0.5	0.5

For the parameters given in Table 6.1 we solve this system numerically and show that the solution converges, Figure 6.13 (a). Finally, we estimate the average probability of content distribution for nodes departing from the network given by

$$p_{avg} = \frac{p_{10}\lambda_{10} + p_{20}\lambda_{20}}{\lambda_{10} + \lambda_{20}}. \quad (6.19)$$

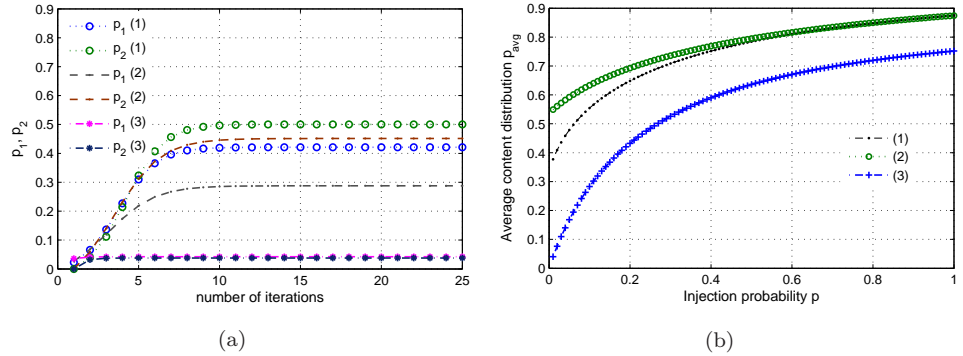


Figure 6.13: Convergence of the content distribution probabilities, p_1 and p_2 , for the two stations. (a) Average probability of content distribution in a two-station cyclic network. (b)

where $p_{i0} = (1 - q_{ij})p_i$, $i, j \in \{1, 2\}$, $i \neq j$, and show the results in Figure 6.13 (b).

As expected, the amplification effect is obvious in all three cases; however, for small variations of the arrivals rate and for low value of p , p_{avg} significantly varies, for example note that the values are 47%, 59% and 17% for $p = 2\%$.

6.4 Conclusion

This chapter focuses on content distribution in an open system where pedestrians exchange contents over short range radios in an opportunistic manner. We proposed an analytic queueing model to study the performance of content distribution in smaller areas where high connectivity of nodes can be assumed. Our findings are the following:

- Epidemic dissemination is found to be feasible even in critical cases for the system, when the inflow of nodes carrying the contents is relatively low.
- We also observe that the system provides virtual storage for the contents, i.e. contents reside in the system over long proportion of time, without support of a stationary node that could assist the distribution.
- The proposed model is validated by comparison with mobility traces.
- The model can also be used for areas where the internal mobility affects connectivity of nodes.
- We show a method to model larger areas as a queueing networks consisting of basic building blocks and study content distribution in two- and four-station networks.

In the future, we would like to analyze the properties of more complex queueing networks and propose a framework how to build arbitrarily large mobility models from the basic queueing models.

7 Epidemic content distribution

In opportunistic networks, frequent topology changes and intermittent connectivity make routing a challenge. A variety of opportunistic routing schemes have been proposed and epidemic spreading is central to many. Epidemic content distribution schemes are able to achieve minimum delivery delay at the expense of increased use of resources, such as buffer space, transmission power, and bandwidth. In order to exploit trade-off between delivery delay and resource consumption, different schemes limit the number of hops for contents to be carried. Early performance studies of epidemic routing schemes used simulations [50, 51]. Adopting the principles of epidemic modeling from the field of mathematical biology to study spreading of diseases, stochastic modeling has become a common approach.

In this chapter, we empirically study the performance of epidemic content spreading by using real-world mobility traces. Then, we consider an analytic model proposed in [52], and examine if this homogeneous model can be utilized to evaluate the performance of opportunistic networks. We consider a basic epidemic scheme, where all nodes participate in content forwarding.

7.1 Opportunistic content distribution model

Application scenario

The application scenario we consider here is that of disseminating information by utilizing opportunistic contacts based on user interest. Sharing local news, traffic and tourist information in public areas, public announcements at massive events, or mobile advertisements are common examples where this can be used. From the perspective of a publisher, questions of interest could be: How many users will the information reach in a period of one hour?, or what is the probability that the information will reach a certain number of users? Such questions can be answered by analytic modeling of the information spreading.

Homogeneous system model

We consider a network \mathcal{N} with $|\mathcal{N}| = N$ mobile nodes, equipped with short-range radios and moving in a bounded area. The network is assumed to be relatively sparse, with node density insufficient to establish a connected network. The data is stored and carried by nodes, and transferred through intermittent contacts

occurring owing to node mobility. Hence, the network is modeled as a series of pair-wise contacts.

Let us introduce the definitions and assumptions that we will use in this text. The *contact time* is the duration of time when two nodes are in transmission range of each other. The *inter-contact time* for a pair of nodes is defined as the time elapsed between two consecutive contacts.

We assume that the mobility of nodes is such that the inter-contact times between any pair of nodes can be modelled by independent identically distributed (i.i.d.) random variables that are exponentially distributed. Then, we assume that nodes in the network are *homogeneous*, that is, all the nodes have the same mobility and contact patterns that follows the same exponential inter-contact distribution with average rate λ .

The content spreading scheme works as follows. At time $t = 0$, there is a single node in the network that possesses the content item and all other nodes in the network are interested in obtaining it. Nodes that obtained the content are willing to forward it to other nodes they meet. We study the performance by investigating the time it takes for the content to reach all the other $N - 1$ nodes. The transmissions are assumed to be instantaneous and every contact results in a successful transmission.

We are interested in two metrics which characterize the process of content distribution, namely *overall* and *individual delivery time*. Consider a network \mathcal{N} and an arbitrarily chosen node i , $i \in \mathcal{N}$. Given that the content is available at i at time $t = 0$, the *overall delivery time*, denoted by T_{odt} is the time until the content has reached all the other $N - 1$ nodes. The time until a node j , $j \in \mathcal{N}$ has obtained the content is the *individual delivery time*, T_{idt} . From a performance perspective, T_{odt} measures the performance of the entire system, while T_{idt} is a measure of the system performance seen from an arbitrary node.

Borrowing the terms from epidemic modeling [53], we denote nodes that carry contents as *infected*, and nodes that are interested in obtaining contents as *susceptible* nodes. In our model, once a susceptible node is infected, it stays in that state for the remainder of the epidemic process. Thus, the model can be classified as a *susceptible-infected* epidemic model.

Epidemic model

In the field of epidemic modeling, there are two main approaches to analyse spreading: stochastic and fluid-based modeling. Stochastic models are preferable when studying networks of small scale, since they allow some randomness in the final number of infected. The fluid models present a deterministic approximation of the stochastic spreading and can therefore only produce accurate results for networks of larger scale. From an engineering point of view, only stochastic models are able to predict the distribution of time until a certain percentage of network has been infected. Furthermore, stochastic models have shown to be advantageous for modeling a network in which the contact structure contains small complete graphs: an

example is a social network. Herein, we consider a stochastic model for content distribution, based on a continuous-time Markov chain.

Let the random variable $X(t)$ be the number of infected nodes at time $t, t \geq 0$ with $X(0) = 1$. Since all the i infected nodes spread the content further, the process $\{X(t); t \geq 0\}$ is a pure-birth process with with rates $\lambda_i = i(N-i)\lambda$ for all the states $i = 1, \dots, N-1$, as depicted with the Markov chain in Figure 7.1.

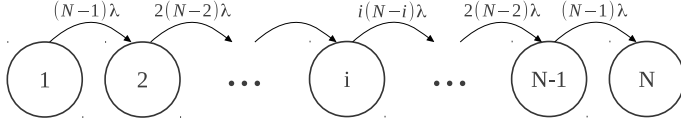


Figure 7.1: The Markov chain for the epidemic scheme.

T_{odt} is the time it takes the system to reach the absorbing state $X(T_{odt}) = N$. The time the system spends in each transient state i is exponentially distributed with the expected value $1/\lambda_i$. and the average absorption time is given by the sum: Denote by $R_{i,i+1}$ the time the system spends in state i . $R_{i,i+1}$ is exponentially distributed with the expected value $E[R_{i,i+1}] = 1/\lambda_i$. The absorption time is given by the sum of the average times spent in each of the transient states:

$$E[T_{odt}] = \sum_{i=1}^{N-1} E[R_{i,i+1}] = \frac{1}{\lambda} \sum_{i=1}^{N-1} \frac{1}{i(N-i)} = \frac{2}{\lambda N} H_{N-1}, \quad (7.1)$$

where $H_n = \sum_{i=1}^n 1/i$ is the n -th harmonic number.

To obtain $E[T_{idt}]$, denote by the random variable $T_{k,N-1}$ the time until k out of the $N-1$ susceptible nodes have become infected, and introduce the event K that a given node is the k -th to become infected. Since all nodes are identical and inter-contact times are i.i.d., the probability of this event is $Pr\{K\} = 1/(N-1)$ and

$$E[T_{idt}] = \sum_{k=1}^{N-1} E[T_{k,N-1}] Pr\{K\} \quad (7.2)$$

$$= \frac{1}{N-1} \sum_{k=1}^{N-1} E[T_{k,N-1}]. \quad (7.3)$$

$E[T_{k,N-1}]$ is the mean time it takes the Markov chain to reach state $k+1$ and therefore we have

$$E[T_{k,N-1}] = \frac{1}{\lambda} \sum_{i=1}^k \frac{1}{i(N-1)}, \quad (7.4)$$

and

$$E[T_{idt}] = \frac{1}{\lambda(N-1)} \sum_{k=1}^{N-1} \sum_{i=1}^k \frac{1}{i(N-1)}. \quad (7.5)$$

The double sum can be rewritten as

$$\sum_{k=1}^{N-1} \sum_{i=1}^k \frac{1}{i(N-1)} = 1 + \frac{1}{2} + \frac{1}{3} + \dots + \frac{1}{N-1} = H_{N-1}. \quad (7.6)$$

Finally, the expected individual time is then

$$E[T_{idt}] = \frac{1}{\lambda(N-1)} H_{N-1}. \quad (7.7)$$

Expressions (7.1) and (7.7) describe epidemic spreading with respect to content delivery times. In the next section, we empirically analyse the spreading in four scenarios, by means of simulation.

7.2 Analysis with mobility traces

Mobility Datasets

Herein we describe the mobility traces used in our study. First we detail the contexts where the datasets were collected and the acquisition methodologies used, then we describe our methodology of obtaining inter-contact times from the traces.

To cover various scenarios, we use four experimental data-sets different in time granularity, number of participants in the experiment and in duration. The datasets report pairwise contacts between users moving in relatively restricted areas: a conference venue, a university and in office buildings. Note, however, that the areas are not strictly bounded, thus users may leave the areas and return after longer periods (even days). Below we explain how we treated those cases. The characteristics of these sets are summarized in Table 7.1.

Infocom

Mobility traces [54] were obtained during four days at Infocom 2006. The dataset reports direct contacts between a group of 78 attendees of a workshop, who were carrying iMotes. The scanning interval was 120 seconds. Thus, it is likely that many shorter contacts were not recorded. Also, due to the scanning cycles, contacts between two users scanning simultaneously are missing. Therefore, we assume that two nodes were in contact if either of the nodes reported that event. As our model assumes a closed system (no nodes leaving), we consider only the time intervals when most of the nodes were active and seen by other users. The experiment lasted for four days; we extracted from the trace only the contacts during daytime: between 9:00 and 18:00 on the first and the third day, between 9:00 and 21:00 on the second, and between 9:00 and 16:00 on the fourth day.

Table 7.1: Mobility traces characteristics.

	Infocom	Humanet	Supsi	Milano
Context	conference	company	institute	university
Duration of trace (days)	4	1	11	7
# contacts (entire trace)	79663	46032	455768	11895
# contacts (single day)	31517	46032	37230	1737
Scanning interval	120 s	5 s	10 ms	1 s
Number of nodes	77	52	34	44
Max # contacts per node	73	46	9	31
Average # neighbors per node	72	30	10	32
# observable node-pairs	2742	680	176	613
total # node pairs	3003	1326	561	820

Humanet

The trace [49] has already been used in section 6.2; for convenience, here we give an overview of the traces. The dataset describes human mobility of participants in an office building. The data collection was carried out in a company building and contains traces of 52 participants, company employees, during one working day. The users were carrying customized-Bluetooth devices, which were scanning every 5 seconds to capture direct contacts with other devices. For each user, contact entries contain the time when the contact started and when it ended. First, we processed the trace to account for all the contacts recorded by either of the two nodes, and when both nodes recorded the same event, we took the entry with longer contact duration. Some entries contained contacts of zero duration; if either of two nodes reported a contact with non-zero duration, we chose that entry. The next step was to merge multiple consecutive contacts of zero duration if their inter-contact time was shorter than one second into a single contact with the duration equal to the sum of their inter-contact times, and finally, we omit contacts that occurred before 10:00 or after 19:00.

Supsi

The entire dataset [55] includes contacts between 39 participants from three institutes, located in two different buildings. The experiment was carried out in December 2010 and lasted more than three weeks. We use records of eleven days when the largest number of contacts was recorded. Proximity information was collected by sensor nodes, carried by the users. The nodes were configured to have a transmission range of 5 meters and perform neighbour discovery every 10 milliseconds. Similarly to the previous traces, we consider only contacts from 9:00 to

18:00. This comes from the assumption that the contacts took place in the area of interest, and that they represent real mobility of people, as some devices collected contact information during the night when left by the users in the offices. This leaves records of 34 users in total; the number of active users per day varied from 13 to 27.

Milano

Milano dataset [56] was collected at the University of Milano in November 2008 from 44 mobile devices carried by faculty members, graduate students, and technical staff. The experiment area comprised offices and laboratories located in a three-floor building, and nearby premises where participants took breaks during lunch times. Contacts were logged by devices operating with a transmission range of 10 meters and a configurable scanning interval of around one second. By using the same procedure of filtering out sparse contacts during the night or during the days when few participants were active, we extract only the contacts during work hours from 9:00 to 18:00 over twelve days.

Aggregate inter-contact time distributions

Note that all traces capture direct contacts between the experiment participants, and, aside from the *Infocom* trace, with scanning intervals in the order of seconds. Due to the long scanning interval, the *Infocom* trace may be missing shorter contacts.

We calculate the inter-contact times between any two nodes, and assume that all the samples come from one and the same distribution, the *aggregate* inter-contact time distribution. The distribution of samples of inter-contact times for a specific pair of nodes is denoted by *pair-wise* inter-contact time distribution. The aggregate distributions are plotted in Figure 7.2 (the figure shows complementary cumulative distribution functions (CCDFs)). The average inter-contact times of these distributions are: 2347 (*Infocom*), 312 (*Humanet*), 323 (*Supsi*) and 7996 seconds (*Milano*) ($\bar{\tau}_{ag}$ in Table 7.2). Only the *Milano* trace seems to resemble exponential distribution, and only up to around 6 hours (found by looking carefully into a lin-log scale). All distributions exhibit fast decay after a certain value (usually order of hours), which however, could simply be an artefact of the finite duration of the traces.

Table 7.2: Estimated average inter-contact times [s].

	Infocom	Humanet	Supsi	Milano
$\bar{\tau}_{ag}$	2347	312	323	7996
$\bar{\tau}_{i,j}$	4386	1473	2397	14841
$\bar{\tau}_{i,j}^C$	15187	16346	4495	66445

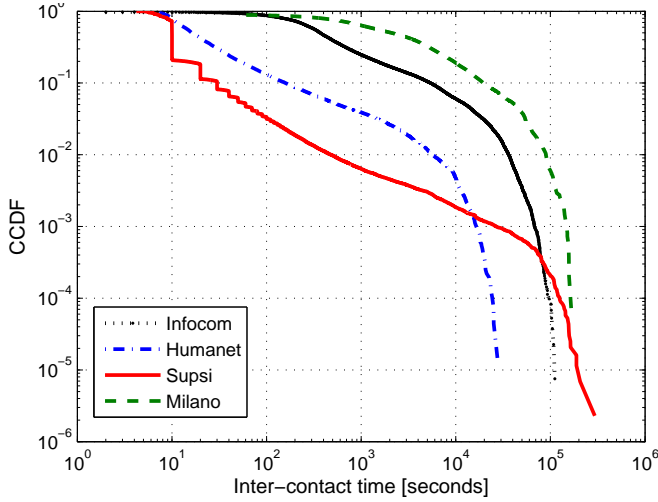


Figure 7.2: CCDF of aggregate inter-contact times.

In opportunistic networking, accurately characterising inter-contact times between nodes is crucial for evaluating system performance. In earlier works, the common approach has been to look at aggregate distributions. However, recent studies such as [57, 58] indicate the risk of treating aggregate distributions as representative of pair-wise distributions. The authors in [58] prove that aggregating various pair-wise distributions can lead to false conclusions on the characteristics of node interactions on a pair level. We confirm this in the following section.

Experimental evaluation

In this section, we assess the capability of the homogeneous epidemic model to capture the process of content spreading in real-life scenarios. We simulated four scenarios by replaying the pre-processed traces in section 7.2. For each of the traces, we choose a single day when the nodes were most active, seen as the number of contacts recorded during that day. The reasons for this are twofold: first, to observe the spreading we needed enough interaction between users, and the second, some nodes were missing from the traces during multiple days. *Humanet* trace is only one day long; for *Infocom* and *Milano* we choose the first day and for *Supsi* the eleventh. The number of nodes during those days was 72, 52, 19 and 32, for *Infocom*, *Humanet*, *Supsi* and *Milano*, respectively. The spreading works as follows. We start by infecting a single node and evaluate the time until it infects all other nodes. The same process is repeated for all the nodes in the trace. To account for the daily variations, nodes spread new content every hour during the active part of the day. We consider only the simulation runs when all the nodes were eventually infected and find the average overall delivery times and individual delivery times. Cumulative distribution functions (CDFs) for individual delivery times are plotted in Figure 7.3.

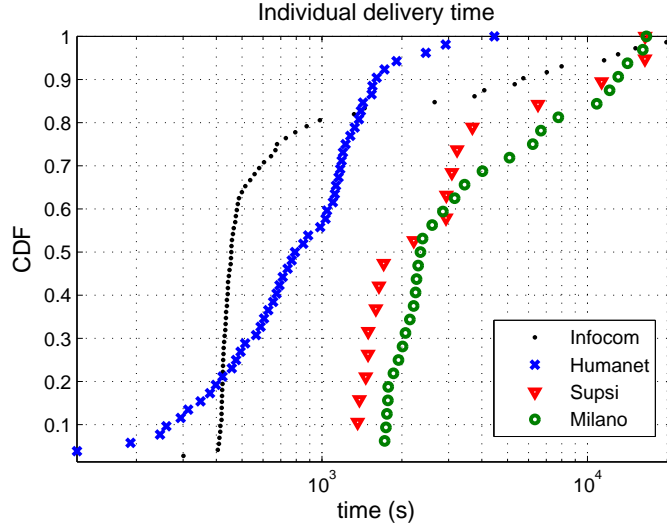


Figure 7.3: CDF of the individual delivery times.

The analytic model is an efficient tool to estimate the system performance; its simplicity stems from the fact that it requires only two input parameters: the number of nodes in the network and the node inter-contact rate. In order to validate the analytic model, we compute the same metrics, overall and individual delivery times given by formulas (7.1) and (7.7), and assume that node interactions can be described by the aggregate inter-contact time distributions. The inter-contact rates are reciprocal to average inter-contact times. Figure 7.4 depicts the simulation results and the computed delivery times (denoted by model^a).

We observe large discrepancies between simulation results and the delivery times predicted by the model. The average overall delivery times obtained from the simulations are: 359 minutes (*Infocom*), 74 minutes (*Humanet*), 275 minutes (*Supsi*) and 278 minutes (*Milano*); while the model predicts delivery times: 316, 54, 118 and 2012 seconds. Clearly, the model does not match any of the scenarios, and it underestimates the overall delivery time for the *Supsi* trace by three orders of magnitude. With respect to the average individual delivery times, the situation is similar; the simulation yields: 2089, 993, 4264 and 4291 seconds, and the model gives: 160, 28, 62 and 1039 seconds.

The explanation for this lies in several factors:

1. The aggregate inter-contact time distribution is not representative of the pairwise inter-contact distributions in any of the examined traces. This can be seen from the aggregate distributions for *Humanet* and *Supsi* in Figure 7.2. Their average inter-contact times are relatively short (order of minutes), while the distributions are long tailed. This is due to finite duration of the traces: pairs that meet more frequently will contribute more samples of their inter-contact times.

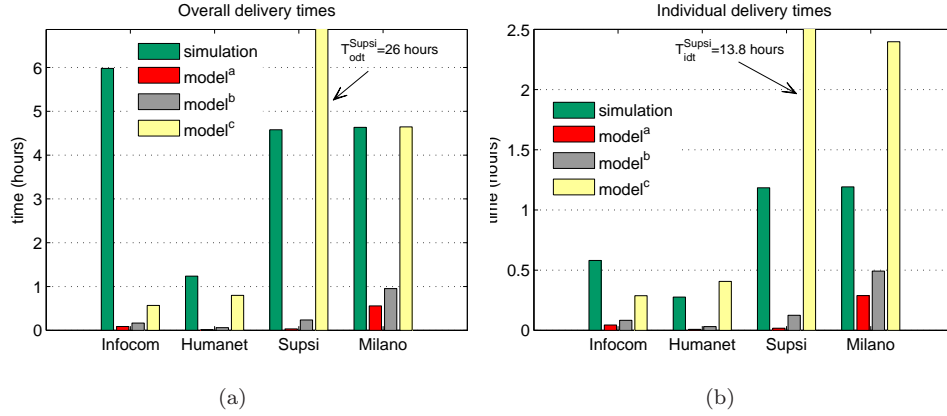


Figure 7.4: Comparison of the overall (a) and individual (b) delivery times.

2. Many node pairs never meet. In some scenarios, we see that even the most "social" nodes meet very few other nodes (see the maximum number of neighbors or number of observed node pairs in Table 7.1), and hence, not all of their inter-contact times are observable.
3. To estimate spreading times, we calculated the delivery times by averaging only over those simulations in which all the nodes were infected. In theory, the average overall delivery times would be infinite, since some nodes never get infected.

We investigate the first two findings in further detail in the following sections.

Pair-wise inter-contact time distributions

In all four traces, we have seen that the aggregate inter-contact time distribution does not give a complete view of the contact patterns in the network. Thus, we look at inter-contact times on a node-pair level. However, fitting different distributions for each node pair would lead to an intractable model. Hence, on a node-pair level some approximation is usually assumed. The important part is that all distributions have exponential decay or at least exhibit exponential tails. For each pair of nodes in a trace, we find the average inter-contact time and plot the distributions of these average times in Figure 7.5. For all the traces, log-normal distribution seems to be a good fit; we observe that the tails of the empirical data are bounded by log-normal and Weibull curves. We then applied curve fitting with log-normal and estimated the average inter-contact times. The average values are given in Table 7.2, denoted by $\bar{\tau}_{i,j}$. By plugging these values in the formulas, we find that the delivery times are still underestimated, although they yield better estimates than in the case of inter-contact rates calculated from the aggregate distributions. The overall delivery times are 591, 256, 882 and 3736 seconds, and the average individual delivery times are 300, 130, 465 and 1928 seconds (model^b in Figure 7.4).

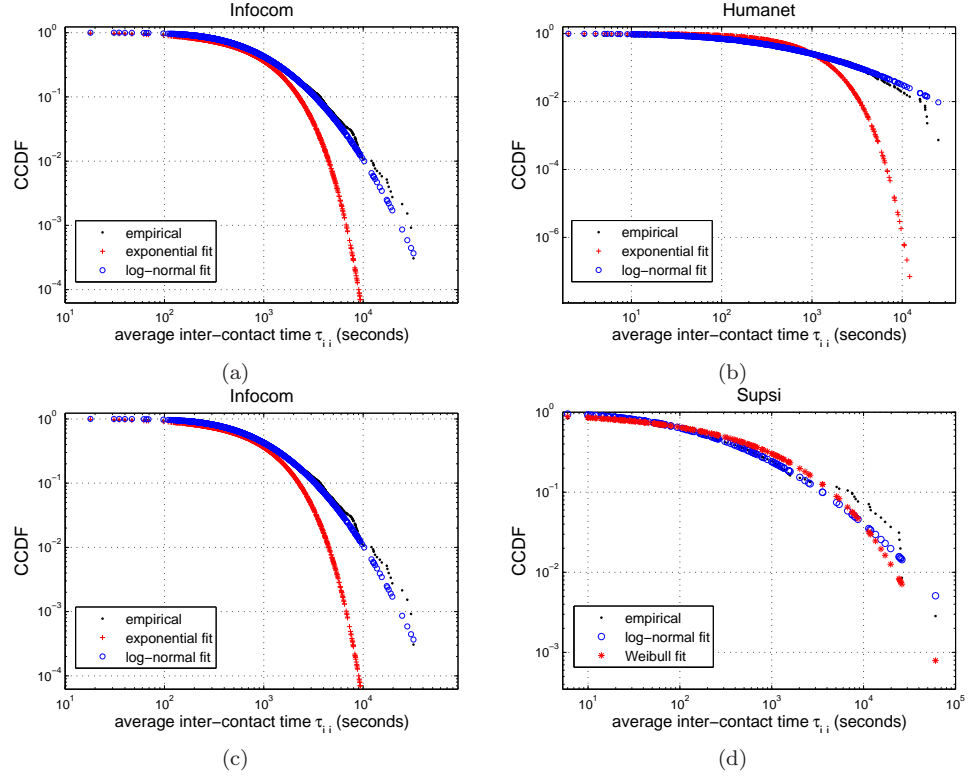


Figure 7.5: CCDF of average pair-wise inter-contact times: Infocom (a), Humanet (b), Supsi (c), and Milano (d).

Clearly, node contacts are too heterogeneous: notice from Figure 7.5 that average inter-contact times for different pairs differ by two orders of magnitude. Still, we want to examine if, by simply treating the traces in a different way, we can improve the estimation using the homogeneous model.

Compensating for the missing contacts

In a network of N nodes, there are $\binom{N}{2}$ node pairs, and each pair can generate different pair-wise inter-contact time distributions. Our idea is to model contact patterns with an average inter-contact time for each node pair. Then, contact patterns in the network can be described by the *contact matrix*

$$\mathbf{T} = \begin{bmatrix} 0 & \bar{\tau}_{1,2} & \cdots & \bar{\tau}_{1,N} \\ \bar{\tau}_{2,1} & 0 & \cdots & \cdots \\ \vdots & \bar{\tau}_{i,j} & \ddots & \vdots \\ \cdots & \cdots & \cdots & 0 \end{bmatrix},$$

where $\bar{\tau}_{i,j}$ is the average inter-contact time for a pair of nodes (i, j) . \mathbf{T} is a symmetric, zero-diagonal matrix since $\bar{\tau}_{i,j} = \bar{\tau}_{j,i}, \forall (i, j)$. Thus, to describe a network we need $n(n-1)/2$ matrix elements, but many node pairs are missing from the traces. For example, only 30% of all node pairs in the *Supsi* trace are observable. This raises the question how to model interaction between those node pairs and to fill in the missing elements of the contact matrix.

To account for the missing pairs, we use the following method: assume that all the nodes i and j , whose contacts are not captured in the processed trace, meet with some average inter-contact time T_m . The number of observed and the total number of node pairs is given in Table 7.1. First, we set the value T_m to be equal to the duration of the entire trace: 36 hours (*Infocom*), 9 hours (*Humanet*), 103 hours (*Supsi*) and 62 hours (*Milano*). Then, we calculated the average inter-contact times for the traces by averaging over the elements of the contact matrix; these values are given in Table 7.2, denoted by $\bar{\tau}_{i,j}^C$. The results for delivery times are plotted in Figures 7.4 and 7.6 (model^c). Figure 7.4 shows that the proposed method is unable to accurately estimate the delivery times in any of the scenarios. In case of the *Infocom* trace, the analytic model underestimates both overall and the individual delivery times, while for the *Supsi* trace, both times are overestimated. For the *Milano* trace, the model gives good estimation of the overall delivery time, while it significantly overestimates the individual delivery time. The only scenario where we observe a fairly good approximation for both delivery times is the *Humanet* scenario. However, the inconsistency of the method makes it unsuitable for use on an arbitrary trace, when the properties of the trace are not known a priori. This implication is also evident from Figure 7.6; the model does not capture the evolution of the epidemic process.

We also tested if filling the contact matrix with a different value for T_m would give a better fit. Curves in Figure 7.6 (a, b, d), denoted by model^{c*}, correspond to the cases where inter-contact times T_m are equal to the length of a work day (around 9 hours). Although the curves in Figure 7.6 (c, d) show asymptotic behaviour in the beginning, it cannot be estimated when the simulated spreading starts to deviate from the model. For example, an accurate estimation of the time until a certain fraction of the network is infected, e.g. 80% of nodes in the *Milano* scenario, would not be possible by using this model.

The usefulness of the homogeneous model is in its simplicity, as it requires only two input parameters. However, we conclude that the homogeneous model is not accurate enough to be used for studying epidemic spreading in general, and we show methodologically, what recent studies use as a starting point and assumption but without proving, that node heterogeneity cannot be neglected when evaluating the network performance.

7.3 Discussion

This chapter mainly relates to the performance evaluation of epidemic content spreading. Epidemic models, adopted from the field of mathematical biology, are

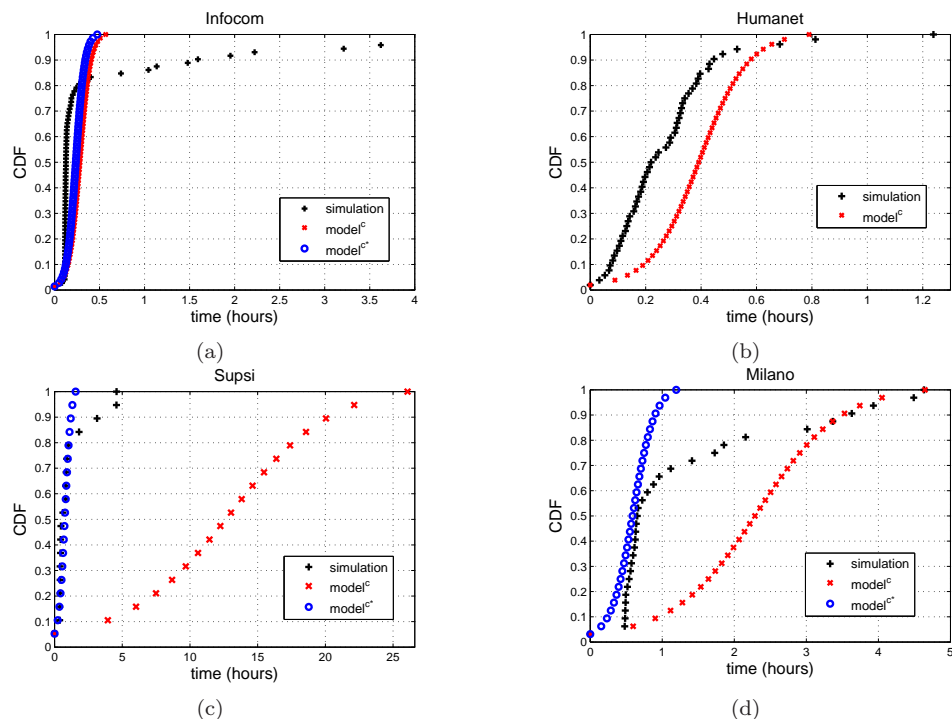


Figure 7.6: CDF of infected population: Infocom (a), Humanet (b), Supsi (c), and Milano (d) trace.

widely used in networking to study spreading of messages. The models belong to one of the two categories: stochastic or deterministic models. Our study focuses on a stochastic Markov model for epidemic content distribution in opportunistic networks, proposed in [52]. A Markov model was also used in [59] to model the message delay in ad hoc networks until a specific destination was reached. The other line of work in stochastic modeling uses transient analysis of random graphs, as in [60], where the hop-limited broadcasting of messages was analysed. Studies such as [61], [62] use ordinary differential equation models, and consider the epidemic spreading process as a fluid flow. Common for all these works is that they assume homogeneous system. Recently, there have many been efforts to characterise epidemic spreading in heterogeneous systems. Heterogeneity is introduced by separating network nodes into multiple mobility classes in [63], [64], or modeling completely heterogeneous networks, as in [65]. However, it is debatable whether using these analytic models gives enough insight over simulations to account for their complexity.

7.4 Conclusion

We empirically evaluated the content delivery times by using four mobility datasets, chosen to represent a small system of pedestrians, moving in a relatively bounded area, and compared the empirical results with analytic model. We proposed three methods of treating the statistical data obtained from the traces. Our main finding is that a homogeneous model is unable to accurately capture the epidemic process in real-life scenarios and our future work will aim at modeling epidemic spreading in heterogeneous systems by using stochastic models.

8 *Conclusion and future work*

8.1 Conclusion

Opportunistic networking is seen as a promising solution for scalable content distribution and for enabling communication in infrastructure-less environments by utilizing sporadic contacts between human-carried mobile devices and their ability to store, carry and forward contents. This thesis presents a study of several aspects of opportunistic networking. Our main findings are the following.

- We presented the design of a middleware for opportunistic content dissemination, that is based on a publish/subscribe paradigm. We also implemented our middleware on top of the Android platform and evaluated the system performance in a small-scale controlled environment, measuring the energy consumption and profiling of the solicitation protocol. Our results confirmed the feasibility of an opportunistic system.
- We proposed the framework to study mobility with respect to the structure of mobility and the constraints which determine human movement. We argued that a model needs to be representative for a specific scenario, and we proposed an analytical queueing model for content dissemination in small urban areas. The basic model can be used to form more complex models to represent larger areas.
- Finally, we considered epidemic content distribution and empirically evaluated the content delivery times by using real-life mobility traces chosen to represent a small, homogeneous system of pedestrians. The comparison of the empirical and analytical results showed that a homogeneous stochastic model for content distribution is unable to accurately capture the epidemic process in real-life scenarios.

8.2 Future work

The work presented in this thesis has answered some important questions, but has also raised many new and interesting ones, which we think deserve a closer look. In particular, in our future work we will address the following topics.

- **Imperfect epidemic queues**

In our analytical model, we assumed that the content transfers inside the modeled area are instantaneous. This, however, may not be true as the transfer time may not be neglected, owing to node and service discovery, as well as internal mobility inside the area. We will revisit this assumption and study imperfect node infection in queues.

- **Mobility framework**

We will implement a library of basic building blocks for mobility, which can then be used to form arbitrarily large mobility models and study mobility and content distribution in larger urban areas.

- **Epidemic modeling of heterogeneous systems**

We will also aim at modeling epidemic spreading in heterogeneous systems by means of stochastic modeling.

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