Opportunistic Routing in Intermittently Connected Wireless Mobile Social Networks

by

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ABSTRACT

Consumer electronics such as cellular phones and portable computers with short-range communication capabilities have enabled the large-scale information dissemination through user mobility and contact, without the assistance of communication infrastructures. In such a new communication paradigm, one challenge is to determine when and how to forward a message to the destination, possibly through a series of third parties. This problem has attracted a lot of attention in the literature lately, with proposals ranging from epidemic to single or multi-copy spray and wait or focus strategies. However most existing work assumed independent or identically distributed mobility. Observing most human mobility and interaction are interest-driven in the real world, in this research, we evaluate the performance of these schemes with an interest-driven mobility model. We further propose to take the user interest into account when determining routing strategies to further improve the performance of these schemes for mobile social networks. Simulation results have demonstrated the efficacy of the interest-aware routing strategies.

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I would like to thank:

Everyone, for being there.

DEDICATION

to everything that makes us doubt.

Chapter 1

Introduction

Cellular phones, tablet PCs and other portable consumer electronics have become increasingly available and affordable. According to the International Telecommunication Union (ITU), the number of mobile phone subscriptions neared 6 billion by the end of year 2011 [1]. This trend creates many exciting opportunities for consumer communication and networking applications. Specifically, short-range communication capabilities such as Bluetooth and Wi-Fi have enabled the large-scale dissemination of critical information through user mobility and contact, even when a communication infrastructure is temporarily compromised, not cost-effective, or unavailable, e.g., at disaster sites or in developing regions. This new communication paradigm has attracted a lot of attention from both academia and industry in the last few years.

One of the biggest challenges in this new context is to route messages through a series of intermittently connected nodes. Unlike traditional store-and-forward networks, in which the existence of an end-to-end path is a given assumption, in mobile social networks such a path may not exist between a source and a destination most of the time. However, intermediate nodes can store, carry and opportunistically forward a message to the next node that would potentially deliver the message or repeat the same process. In other words, by utilizing user mobility we can achieve a much higher chance of delivery in scenarios where the traditional ad-hoc routing protocols are practically dysfunctional. It is obvious that the routing strategy will determine the usability and performance of mobile social networks with regard to user mobility and interaction patterns.

Although the messages disseminated in mobile social networks, e.g., daily news or personal messages, are usually delay tolerant when compared with the traditional data exchange applications, these messages should be delivered to the destination in a reasonably reliable manner and within a certain time limit, above which the information may become useless. Many routing strategies have appeared in the literature lately, ranging from random or epidemic routing to single or multi-copy Spray and Wait or Focus, as well as their variants. However, most existing work assumed an independent and identically distributed (i.i.d.) mobility model, although the observations from the real world suggest that human mobility and interactions are partly driven by the user's interests and the structural features of the environment.

1.1 Main Contributions

The contributions of this thesis are threefold. First, we propose a simple but effective Interest-Driven Mobility Model (IDMM) inspired by the real-world measurement results and social networking theory. Different from other existing mobility models, IDMM focuses more on users as individuals and the implicit formation of communities through their inclination towards certain salient locations based on their personal interests. We then study our proposed mobility model through simulation and verify that the movement and contact patterns of network users are neither independent nor identical. Second, we use this mobility model to evaluate the performance of previously proposed routing strategies in intermittently connected wireless mobile social networks such as “Spray and Focus” [2], and identify the effects of interest-driven human mobility on their performance. Finally, by proposing an enhanced interest-aware Spraying technique, we show that the performance of the existing schemes can be considerably improved from the network's point of view. More specifically, our algorithm is able to reduce the total number of transmissions without degrading other important performance metrics, when compared with the existing schemes. By reducing the total number of transmissions, we are lowering the bandwidth and power consumption of the network as a whole.

1.2 Thesis Organization

The remainder of this thesis is organized as follows. In Chapter 2, we briefly overview mobile social networks and their performance metrics, and review related work on mobility models and routing strategies. An interest-driven mobile social networking framework and an interest-aware routing strategy are proposed in Chapter 3. The performance of the proposed strategy is evaluated in Chapter 4 and compared with other existing strategies in both i.i.d. and interest-driven mobility models. Concluding remarks are given and discussed in Chapter 5.

Chapter 2

Background and Related Work

Fall et al. formalized and proposed a general framework for Delay Tolerant Networks (DTN) [3]. The early applications and research work in this area, mainly evolved around scenarios in which node mobility is deterministic, such as the interplanetary Internet [4]. In certain scenarios node mobility could even be *planned* by the scheme design, e.g., mobile elements in message ferrying applications [5]. Only recently, due to the growing popularity of hand-held devices such as cell phones and Internet tablets, a new class of DTN has become the center of attention in the research community, Mobile Social Networks (MSN). Despite infrastructure-based networks, such as cellular and 3G networks, being the most common method of communication, opportunistic mobile social networks can be beneficial in certain situations. In [6], Crowcroft et al. enumerated a few of such situations. Firstly there are situations in which the network infrastructure may be temporarily or permanently absent, e.g., due to natural disasters or due to the high cost of the infrastructure in developing countries. Even in presence of an infrastructure-based network, being able to rely on a delay tolerant network with lower performance standards is certainly more desirable than no connectivity in case of a network outage.

Here we focus on MSN, in which user **mobility** and their **social relations** are the key elements in understanding the behavior and analyzing the performance of such networks. In the following sections, we will go over the relevant work in each of these two research trends, namely social network modeling and mobility modeling. Putting the pieces together in the last section, we will review the previous work on designing the routing protocols for MSNs.

2.1 Social Network Modeling

In this section we will go through some of the key structural features of human social networks. More specifically, we start by reviwing the literature on Online Social Networks and move on to Mobile Social Networks, enumerating their similarities and differences.

2.1.1 Online Social Networks (OSN)

The recent emergence of many popular online social networking websites and applications has enabled researchers to study the structure and properties of these networks in the past few years. During this process many classic hypotheses about social networks have been observed and verified using massive collections of crawled empirical data from popular online social networks. For instance it has been verified that the diameter of the friendship graph in OSN is often very small, i.e., the well-known "small world" phenomenon [7].

In addition to the verification of well-known properties, the data collected from OSNs have enabled researchers to examine new aspects of social networks such as the formation of communities, power-law distribution of node degrees and existence of hub nodes, etc. These findings certainly call for the design and proposal of new models for the way nodes behave in a social network.

With the discovery of these new structural features, many previous network models proved to be simplistic, creating the need for more comprehensive models. Taking the node popularity as an example, all previous graph models that resulted in a uniform distribution of node degrees, were crossed out by the discovery of power-law distribution of popularity. Graph models such as the preferential attachment method are attempts to mimic the power-law distribution of node degrees. Also, the formation of communities, high clustering coefficient and geographical distribution of long-range edges have led to quite a few explanatory models.

The recent popularity of location based online social services such as Foursquare, has provided the researchers with both the social structure and the spatial information of the users. Examination of this new type of information, has enabled the scientists to bridge the gap between Online Social Networks and Mobile Social Networks. In [8] the authors examined the spatial properties of the social networks of three major online location-based services, namely, Brightkite, FourSquare, and Gowalla. Their measurements suggest a strong correlation between the users spatial properties and their social relationships. More specifically they investigated the probability of a friendship between two users whose home locations are at distance d from each other, i.e., $P(d)$. This relation is often estimated by $P(d) \propto d^{-\alpha}$, since people living farther from each other are less likely to form a social relationship. For all three datasets, they measured the value of α to be somewhere between 0.5 and 1.

2.1.2 Mobile Social Networks

Mobile social networks were the next generation of social networks to attract researchers' attention. Despite their many differences when compared with OSNs, including the mobility of nodes and (often) the locality of contacts, many believed that it is possible to observe the same properties in MSNs, since it is the human behavior that is playing the key role in both classes of networks. Interestingly their intuition has been proved to be true during the past few years, and many of social networks' properties were observed in mobile social networks despite their differences. We will review some of these similarities in the following subsections.

Before going through a list of these important characteristics, we need to point out some of the major challenges in measuring and analyzing different aspects of mobile social networks. An obvious difficulty would be an appropriate redefinition of classic terms such as node degree and graph diameter in these dynamically changing structures. For instance a network of mobile users based on their Bluetooth interactions might be a disjoint graph at any instance of time. However, by allowing a certain amount of delay in message delivery, the dynamic structure of the graph will make many connections possible, which might have not been possible in any snapshot of the connectivity graph.

2.1.3 MSN Characteristics

Degree distribution

In [9], by examining the Reality Mining dataset, the authors showed that the node degree in an MSN has a power-law distribution ($\lambda = 1.05$) among low-degree nodes. They defined node degree as the total number of nodes encountered by a certain node during the experiment. Interestingly they noticed an exponential decay ($\lambda = 5.8$) in the node degree CCDF for high-degree nodes, i.e., nodes with degree higher than 19. The reasons behind this two-phase phenomenon are out of the scope of this thesis. The interested reader can follow this discussion in [10] where the authors proposed an explanatory model for network formations based on optimization problems.

Clustering coefficient and communities

Existence of communities, is one of the most well-known and thoroughly studied structural features of the human social networks [11]. Due to the nature of human relationships, two people who have lots of friends in common, are more likely to be in a friendship relationship. Therefore a high clustering coefficient and frequent appearance of triangular structures (known as triads), are common features of human social networks. Based on the same intuition, various distributed and centralized methods have been proposed to extract the community structure of mobile social networks and exploit that information to improve the opportunistic routing performance [12, 13]. Three distributed community detection algorithms, namely Simple, K-Clique and Modularity are evaluated in [13] and are shown to be up to 90% as precise as centralized community detection algorithms. In [12] the authors used Simple and K-Clique as their distributed community detection methods and exploit the results to implement a multi-point asynchronous communication protocol for publisher/subscriber scenarios.

Graph diameter and average hop count

The "small world" property of the traditional social networks [14], has also been observed in mobile social networks. Through analysis of synthetic networks and various empirical datasets, authors in [15] showed that the diameter of the temporal connectivity graph of an opportunistic network is often relatively small (between 3 and 6 hops for a network of 40 to 100 users) and conforms to the "small world" phenomenon.

Navigability

Navigability is one of the more subtle features of the human social networks. This property was initially pointed out by Milgram and Travers and their well-known series of real-world experiments [16]. In a nutshell their experiment showed that, despite lacking a clear structure, human social networks are formed in a way that allows for navigation without any general knowledge about the overall topology of the relationship graph. During the experiment, a group of volunteers where asked to send a letter to a certain person in another city without knowing the receiver's address. Knowing only his name and occupation, the volunteers would forward the letter to someone they already knew, who in their opinion had a higher chance of knowing the final recipient's address. The relay user would then repeat the same process in the hope that the letter will eventually get delivered to the destination. The results from the experiment suggested that in many cases the destination did indeed receive the letter, and the forwarding process involved an average of around 6 people, suggesting that the average path length obtained by this form of opportunistic forwarding is much smaller than the size of the social network. This is clearly an essential property from the routing point of view. This property allows for proposal of routing protocols, that by relying on the local information at every step of the path, can perform reasonably well when compared with fully-informed protocols.

Building on the work of Kleinberg in [17] who proposed a mathematical model to explain the navigability property in social networks, Chaintreau et al. proposed a mathematical model for an opportunistic network of mobile and stationary network users [18]. Through mathematical reasoning, they proved that in the proposed model users can achieve a reasonable routing performance, while the locality of topology information is preserved.

2.1.4 Mobility and Social Interactions

By going through the papers in this research area, one can notice the popular trend that the temporal contact graph in mobile social networks exhibits similar characteristics as the traditional social networks. In other words, since people's mobility and contacts are affected by their social relationships, one may conclude that mobile social networks have inherited these properties from social networks. A simple example would be the fact that being a member of a tightly knit social cluster, e.g., a group of close friends, could often mean frequent physical proximity to its members, hence the formation of a similar cluster in the temporal graph of contacts.

From another point of view, online social networks inherit their characteristics from mobile social networks. That is to say, the mobility of a person can affect their social relationships. As an example, a short trip may initiate new friendships, while a permanent move can lead to the termination of previous relationships. Similarly some structural features of the online social networks, such as the existence of weak links, are attributed to the underlying mobility patterns of its members, therefore it is crucial to study and understand the model mobility patterns that lead to such characteristics [19].

To understand this two-way relationship between mobility patterns and social relationships, we will go through some of the most substantial work in modeling the user mobility in social networks in Section 2.2. Before moving on, it is important to remind the reader that mobile social networks and online social networks are different from many points of view. MSNs are based on physical proximity, therefore many connections may form between complete strangers as they happen to collocate at a certain point of time, while connections in online social networks almost always form based on some prior acquaintance or social similarities. This also introduces a new problem in opportunistic mobile social routing, in which a message may be forwarded by multiple hops, some of which may be strangers to both the sender and the final receiver of the message. Security and privacy are therefore important aspects of mobile social networks, which may need to be handled in a distributed fashion, as opposed to online social networks that benefit from a central infrastructure. Nevertheless, the various aforementioned structural similarities confirm that there is a clear correlation between people's social relationships and their contact patterns. A phenomenon that allows us to improve the performance of routing protocols in mobile social networks.

2.2 Human Mobility Models

Early mobility models such as Random Waypoint (RWP) and Brownian Motion models have been shown to be too simple to capture the complex behaviors involved in human mobility. By introducing models considering highways, obstacles [20], group mobility [21], and many others [22], researchers have considered many interesting aspects of human mobility. Recently, with huge repositories of realistic mobility traces becoming available [23], human mobility has been studied from various new angles. The flight length distribution [24], periodic patterns [25] and spatiotemporal correlations [26, 27], to name a few, suggest that the human mobility patterns are neither independent nor identical, two commonly used assumptions in the literature. In many scenarios people seem to form communities and move around certain hotspots, where the movement of a person *depends* on how other members of the community behave, therefore mobility is not independent. In addition, in many scenarios the mobility patterns vary across the population, from many different viewpoints, i.e., they are not identically distributed. For instance, consider the total number of contacts over a fixed window of time. While some people can be secluded and stationary most of the time, others can be more social, contacting many other people, and acting as a potential relay between isolated users. Obviously, understanding, modeling and utilizing these aspects of human mobility are necessary for the performance evaluation and improvement of wireless mobile social networks.

From one point of view, it is possible to classify social-aware mobility models based on their different levels of movement abstraction. To be clear, a mobility model may indicate (i) how individual nodes move around in a 2D environment with certain trajectories, (ii) how nodes move between *salient* locations, or in an even more abstract way (iii) how node encounters are affected by mobility.

2.2.1 Geometrical Mobility Models

Geometrical mobility models indicate how individual nodes move in a 2D space by specifying the distributions of their positions, velocities and accelerations. Well-known mobility models such as Random Waypoint [28] and Random Walk [29] are instances of this category. As one of the very first attempts to model the sociological aspects of mobility in ad-hoc networks, Herrmann et al. captured the power-law distribution of node degrees as an essential characteristic of social networks, by proposing a social mobility model in [30]. Their method takes a friendship graph as the input and defines *anchors* as social clusters. Every clique in the friendship graph is regarded as an anchor, and common nodes between anchors are scheduled to switch positions periodically, such that all members of each anchor are co-located at some point of time during the simulation. Since moving from one anchor to another can happen in any arbitrary fashion, authors believe that their model is orthogonal to other geographical models such as Random Waypoint and the obstacle mobility model [20]. For the evaluation purpose, they illustrated that if the node degrees are distributed by power-law in the input graph, e.g., a graph generated from the preferential attachment process, the contact graph resulting from their model will preserve that property.

Based on the work by Herrmann et al., in [31] Musolesi et al. proposed the *Community-based Mobility Model* where nodes belong to communities, i.e., initially associated to certain grid regions. Then at each step each node chooses a new region on the grid and picks a random point within that region as a destination for its next *flight*. The region is chosen based on a matrix specifying pairwise social similarities. Each node ranks all grid regions and chooses the one, which is often chosen by other nodes with similar interests. Their model resembles traditional group mobility models, however communities are formed based on social similarities of their individuals and nodes are free to move from one community to another.

As it was described in the past two paragraphs, [30] and [31] were mostly concerned about the social graph structure, i.e., the power-law distribution of node degrees and the formation of communities which in the second paper will also lead to a realistic distribution of inter-contact time. From a different point of view, Chaintreau et al. proposed a network model in [18] following the steps of Kleinberg in proving the navigability of social networks [17]. For this reason they divided the network nodes in two groups, static nodes on grid points, which would satisfy the high clustering coefficient condition, and mobile nodes performing random walks on the grid, whose links to static nodes would represent the long range edges or weak social ties. By calculating a proper forgetting function they were able to mimic the realistic distribution of long range edges, which in turn leads to navigability of the resulting social network.

2.2.2 Location Transition Models

Due to their simplicity in mathematical analysis, location transition models have attracted many researchers' attention. In [26] authors asked a group of volunteers to keep track of the places they visit on campus as a survey. By grouping locations into five different categories: classroom, library, cafeteria, other on campus and off-campus, they were able to extract the transition probabilities of mobile nodes. They also noticed that further dividing the day into two parts (morning and afternoon) will lead to more accurate and meaningful transitions, since people have different motivations for choosing their movement trajectories throughout the day, which may cancel each other off by averaging.

The model proposed by Hsu et al. [26] did not take into account the differences in mobility patterns of individual users. In a recent publication, Jaho et al. proposed a model based on the transition between locations, focusing on individual preferences of mobile users [32]. In this model each node has two sets of probabilities, one for the probabilities of the membership in locality-induced groups (salient locations), and the other for interest-induced communities (contents). These two sets of probabilities somehow represent the profile of each individual, based on which it is possible to calculate the probabilities of more involved events such as a specific content being the most popular one at a specific location. Based on these methods, authors designed a cooperative data dissemination scheme which was able to outperform a selfish scheme in terms of the usability of the data. That is to say, for the network to have a better overall performance, it may be necessary for each individual user to avoid its own locally optimum decision, i.e., retrieving the content of his own highest interest.

Also using the transition model, Chaintreau et al. divided the San Francisco Bay area into a regular grid and evaluated the effect of opportunistic contacts on the age distribution of the down-link data, disseminated throughout a network of mobile users [33]. They extracted the transition probabilities from mobility traces collected from the city cabs equipped with GPS devices. Using mean field theory, they were able to compute the age distribution of the data at different locations with high accuracy, i.e., very close to the resultant distribution from an event-driven simulation of the original traces.

There is a subtle difficulty involved in these methods that is worth mentioning. In [26] volunteers are able to keep track of their current location at the granularity of building names on campus. Also, having defined square boundaries together with the precise GPS locations of the nodes, the authors were able to track the transitions between locations in [33]. However, in some cases we may not have direct access to the *precise* information about the important locations or users' positions, and thus the task of extracting a meaningful transition matrix becomes more intricate. A method of discovering *salient locations* from Cellular Tower Network (CTN) graph is proposed in [34]. A CTN is a graph with cellular towers as its vertices, between which there is an edge if two towers have occurred at the same time in a channel scan performed by any of the users. The weights on the edges are proportional to the total duration of the time in which towers have co-occurred in all traces. The authors then regard each high-weight cluster in CTN as a salient location at which users spent a considerable amount of time. The transition matrix can be computed based on the extracted locations. Even though this model extracts the differences among salient locations and the relative transition probabilities between them, it fails to recognize the different behaviors of the individual users, i.e., users location information is aggregated over the whole population.

2.2.3 Encounter-based Models

At an even higher level of abstraction, encounter-based mobility models are proposed, by which researchers are able to focus on the effect of mobility on social network dynamics. Take the inter-contact time as an example. Given the empirical data collected from a specific environment, we can use statistical methods to find an appropriate mathematical distribution for this parameter. Therefore by fine-tuning the distribution parameters of the model, we are able to generate synthetic encounter traces with a very good precision in that specific scenario. The Encounter-based Mobility Model (EMO) [9] and the Connectivity Trace Generator (CTG) [35] are two instances of encounter-based models.

EMO takes the pairwise distributions of inter-contact times and encounter durations as the input. In addition, the user has to provide the node degree distribution of the desired scenario, based on which an initial friendship graph is constructed. Then for each edge, EMO will generate instances of inter-contact time and encounter duration, turning it on and off until the end of the simulation. One advantage of EMO over CTG is that it considers all pairwise distributions for inter-contact time and encounter duration parameters, instead of a single distribution representing the average behavior of the whole network.

The mobility model we use in this work is based on the Home-cell Community-based Mobility Model (HCMM) proposed by Boldrini et al. [36], which is an enhanced version of Community Based Mobility Model (CMM) proposed by Musolesi et al [31]. Similar to RWP, HCMM mobility happens in epochs, however network users are randomly assigned to certain cells of a grid as their home cell. When at home, a node moves towards a destination cell according to its level of social ties to the members of that cell. While away, nodes will either remain in the host cell with a certain probability or return to their home cells. Thus mobility can be modeled as a Markovian process using multiple transition probabilities of leaving the home cell, and those of returning to the home cell.

As our first contribution in this work, we propose an interest and location-driven mobility model. This model encompasses many essential elements of human mobility such as heterogeneity and spatiosocial correlations. By excluding the notion of a user's *home* cell, which may limit the types of applicable scenarios, we can provide a general mobility framework that is both location and interest-induced. That is to say, in many mobility scenarios such as students on a university campus, users do not necessarily belong to a certain home location to which they will regularly return.

2.3 Opportunistic Routing Algorithms

The complexity of human mobility makes routing in opportunistic networks a challenging problem, since it is not possible to deterministically guarantee the quality of service in such networks. Vahdat et al. proposed the Epidemic routing algorithm in which messages are spread in the network by the means of a viral diffusion, i.e., people will receive a message if they have not received it already [37]. It can be proved that Epidemic routing achieves the maximum delivery ratio and minimum delivery delay under ideal network conditions. However in a realistic scenario channel congestion can significantly degrade the network performance. Furthermore, too many transmissions could affect the lifetime of a network of small devices with limited energy supplies. In order to reduce the overall cost of delivery, two major types of improvement techniques have been proposed in the literature.

2.3.1 Oblivious Improvements

The first approach is to obliviously limit the number of total transmissions by applying branch and bound techniques on the Epidemic routing tree, e.g., setting upper bounds on the hop count, delivery time or forwarding probability. These routing algorithms are therefore simple and impose very little or no control message overhead. In this work, we are interested in the Controlled Replication technique, which is to limit the total number of replications per message in the whole network. This method is also known as Quota-based routing [38]. Simply put, the initiator assigns a token to the message, indicating the total number of replications. As the message is replicated along the way, this token is updated in each copy with the remaining number of allowed replications. Despite being fast and efficient, these approaches on their own, do not take advantage of the underlying structure of the human mobility.

2.3.2 Context-aware Improvements

The second approach is to use a context-aware scheme, in which nodes are not considered equally eligible for delivering a message. These schemes attempt to estimate how "good" a candidate relay node is for delivering a certain message to the destination. Whether it is based on the spatial distribution of nodes [39], history of pairwise encounters [40], or centrality in the social graph [41], a utility metric is a common design element in these algorithms. By using this metric and forwarding the message only to a subset of the nodes they encounter, users can reduce the number of transmissions, without considerable performance degradation. Generally speaking, these context-aware schemes may suffer from a higher space requirement or increased control message overhead. For instance, to calculate the probability of the future encounters based on the past encounters, all users need to store and maintain their history of encounters and perform extra computations.

As presented in the next subsection, oblivious and context-aware approaches are not exclusive and can be put together to create an algorithm that benefits from both their advantages.

Spray Routing

Proposed by Spyropoulos et al. [2], Spray routing algorithms have attracted a lot of attention lately. By design, the routing process is divided into two phases [2], namely

Spray and delivery phases. This distinctions allows for merging of oblivious and context-aware techniques. Since this method is the basis for our proposed routing algorithm, in the following subsections we will review the latest development and variations in the literature, built on top of this common basis.

Spray and Wait

During the first phase the goal is to spread L copies of a newly initiated message among L network users. The source node A, creates L tokens for the message. While the number of tokens is larger than 1, upon each new encounter, A will *forward* a copy of the message along with one token. This way, the total number of replications is limited by $L - 1$. When a user is left with only one token, it will wait and *carry* the message until reaching the destination, hence the delivery phase.

Binary Spray

This simple modification helps speed up the initial Spraying process. Here node A with $L > 1$ tokens of a message is to forward the message with $\lfloor \frac{L}{2} \rfloor$ tokens to the newly encountered node. This process is repeated recursively for all nodes possessing more than one token for the message. One could see that the Spraying trail would look like a binary tree, halving the tokens at each encounter, as opposed to the linear structure of the previous Spray method. As we will mention in Section 3.3, Binary Spray is proved to be the fastest Spraying technique under i.i.d. mobility conditions.

Binary Spray and Focus

During the delivery phase, nodes can opportunistically forward the copy to a neighbor who seems more likely to contact the destination in the near future (i.e., “focus”). In the original paper [39], geographical information is used as the utility metric for making such decisions. This algorithm benefits from the fast spread of a fixed number of messages throughout the network during the first phase, and the geographically-aware forwarding in the second phase. On the other hand, geographical awareness comes at the cost of more advanced hardware and higher energy consumptions rates. This is one of the reasons we propose the use of social information as utility metric, in appropriate scenarios.

According to the detailed study of DTN routing taxonomy by Spyropoulos et al. [42], Spray and Wait uses copy-limited Controlled Message Replication, meaning that the total number of allowed replications for each message is limited. Furthermore, its improved variation "Spray and Focus" also incorporates Utility-based Replication, i.e., the algorithm acknowledges the non-i.i.d. nature of the users' mobility.

Variable Number of Initial Tokens

Another improvement can be made by adjusting the initial number of tokens L at every initiation instance. Tournouz et al. noticed that in certain scenarios network density changes over time, which greatly affects the performance of quota-based routing schemes. In [43] they show how one can achieve a stable performance by adjusting the initial number of tokens according to the network density, which can be estimated locally by every network user. Each source will determine the initial number of tokens based on the perceived network density and the expected delay of the message it created. Also in [44] the initial number of tokens is determined based on the content priority of the message being created. The proposed algorithm, called ORWAR (Opportunistic DTN Routing with Window-Aware Adaptive Replication), considers three classes of content priority and assigns $L - \delta$, L and $L + \delta$ initial tokens to each class in the increasing order of importance.

Message Prioritization

Short contact times in opportunistic networks, together with the low bandwidth of mobile devices, limit the traffic volume at every encounter. As a consequence, exchanging the full list of messages and control messages often becomes impossible, and the prioritization of content becomes inevitable. For instance, based solely on the message size, smaller messages are often sent first since they are more likely to be transferred successfully given the available network traffic volume. In Fuzzy Spray routing [45] Forward Transmission Count (FTC) together with the message size is used as inputs to a fuzzy rule system which determines the priority of every message. The FTC is an estimate of the overall number of replications for a message in the whole network, which can be computed on the fly by every node receiving the message. Messages with lower FTC values, have higher priorities in the message queue. With a similar approach, authors in [46] propose a routing scheme in which the message prioritization is done according to the message TTL, message size and the remaining number of tokens for the message. In this scheme, messages with a higher number of remaining tokens have higher priorities. Also messages with smaller TTL values are given higher priorities, since they need to be delivered as soon as possible.

Proportional Token Assignment

The last improvement we discuss here is the proportional assignment of tokens according to a utility metric, as opposed to the previously oblivious techniques such as Linear and Binary Spray. In [47] authors define "Quality of Node" as a periodically updated weighted average of contact occurrences in fixed amounts of time. This value is then exchanged at every contact and used as a utility metric for a proportional distribution of tokens between the two sides of a contact. A very similar approach is used in Encounter-Based Routing (EBR) with slight differences in terminology [48].

It is important to note that both of these schemes use destination-independent utility metrics. Moreover, they both require a warm-up period since they rely on the history of contacts.

In order to further improve these routing schemes, we propose a context-aware Spray technique, which we will refer to as the “Weighted Spray Routing”. As opposed to the destination-independent replication method used in Encounter Based Routing (EBR) [48], “Weighted Spray” uses a destination dependent utility to enhance the performance of the routing protocol. By analyzing the similarity of personal interests and the social relations between the network users, we estimate the contact probability and use that as a utility metric for relaying messages. As we will discuss later in detail, by incorporating the destination dependent context-awareness into the Spray phase, we are able to reduce the overall cost of the existing schemes significantly, and improve their performance with respect to the overall delivery overhead.

Chapter 3

Mobile Social Network Modeling

In this chapter, we describe two important aspects of our mobile social network model. The first being the **social** aspects of the network users, i.e., how the underlying social structure is constructed for it to be a reasonable representation of a real-world human network. Secondly, we will propose a simple, yet realistic **mobility** model, by identifying some of the key driving forces in human mobility. As we discussed in the previous chapter, mobility and social relationships are tightly coupled in human networks. Our proposed social and mobility models are also closely-knit and can be viewed as a framework for mobile social network modeling.

3.1 Social Interaction Model

By definition, a social interaction is a complex and dynamic relation between two people, which from our perspective in networking research, boils down to the duration and frequency of their contacts over the time. These two metrics, also known as "Contact Time" and "Inter-Contact Time" distributions, are the two major factors in determining the dynamics of a delay-tolerant network. In this section we will develop methods for estimating the level of interaction between two users, and will use this information in the following sections for describing users' mobility and designing more efficient opportunistic routing protocols.

Going over the related work listed in Section 2.2, one can recognize a general trend among most context-aware opportunistic routing schemes, and that is the fact that they all introduce a utility metric that assigns a value $f_m(X)$ to a relay node X as a measure of its eligibility for delivering the message m to the respective destination. In this thesis, we propose a simple and intuitive utility metric, which is based on the personal interests of the network users. In this scheme every person is associated with an interest profile, i.e., a point in the $\mathbb{R}^d$ space, indicating the user's level of interest in a set of d predefined topics/activities, e.g., shopping, music, etc. Based on the fact that two people with common interests are more likely to have social interactions, we use the dot-product of their interest profiles as their potential level of interaction. Therefore if another user has a higher utility metric for delivering a message, it means that his interests match the destination node's interests more closely, therefore he is more likely to contact the destination user and is a better candidate for delivering the message.

It is important to note that the Dot Product model is in fact a commonly used method for social network graph modeling. In [49, 50] the authors conduct a thorough mathematical analysis of a few random dot-product models, and prove that the resultant graphs project many of the human social network structural features. In the "Dense Random Dot Product Model"—one of the proposed models in [49]—the values in the d-dimensional interest vector for any vertex are drawn from $\mathcal{U}^a[0,1]$, where $\mathcal{U}[0,1]$ is the uniform distribution between 0 and 1 inclusive and $a \geq 1$ is an integer constant number. An edge is formed between two nodes A and B with probability equal to $I_A \cdot I_B$ where I_X is the interest vector for user X. The resultant graphs are proved to capture many important structural features of human social networks such as the power-law degree distribution of the nodes, formation of clusters and the low diameter of the network, i.e., the small world property.

3.2 Interest-Driven Mobility Model (IDMM)

Building up on the social structure we introduced in the previous section, we are now able to propose an interest-driven mobility model. Based on the observations from the real world, many researchers have proposed *location-based* mobility models that include the notion of hotspots, also referred to as salient locations. Simply put, hotspots are often lively and popular places where the network density is considerably high, e.g., shopping centers, coffee shops, university campus buildings, etc. An interesting aspect of such social hotspots is the fact that the users at a hotspot often share a common interest. As an example consider a group of people gathered at an art gallery. Due to the nature of this social hotspot, one could argue that members of this group share an interest in viewing art. Therefore when a group of users have interests or activities in common, they are more likely to collocate at certain hotspots, forming a social community. This is one of the reasons why, in the social-aware mobility modeling literature, the notion of geographical hotspots is often coupled with social communities [34, 36].

3.2.1 Community Placement

In this thesis, we use a grid structure and assign attraction profiles to certain cells of the grid as the social hotspots, an example of which is presented in Figure 3.1 and ultimately used as the basis of our simulations[1]. Three types of hotspots are marked on the map, namely, universities and schools (U), shopping centers (S) and the

[1]Map of the Greater Victoria Area, retrieved in 2009 from website `http://maps.google.ca/`

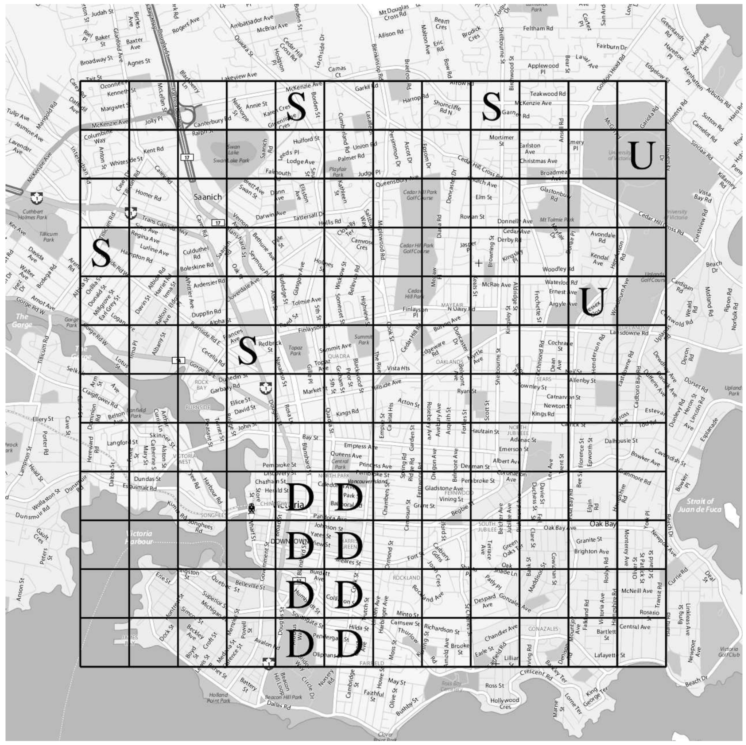


Figure 3.1: Grid layout of hotspots in Victoria

downtown area (D). The attraction profiles are from the same d-dimensional category space as the aforementioned interest profiles in Section 3.1, and they determine how relevant each category or activity is to a particular hotpot.

To elaborate, let us consider the following three activities:

1. Shopping

2. Dining

3. Studying

The weight for the shopping activity is high for shopping centers while the same cannot be said about the studying or dining activity. Therefore $[1, 0, 0]$ would be a reasonable attraction profile for shopping centers, within the context of our 3-dimensional category space: [Shopping, Dining, Studying]. It is important to note that the dot product operation is linear with respect to d in terms of computational complexity. Therefore in scenarios with higher numbers of dimensions in the category space, the computations remain relatively inexpensive.

In addition to the hotspot attraction, travel distances also affect the mobility of a mobile user. Shorter travel distances are more desirable and this factor should play a role in the mobility model—unlike RWP, where the next waypoint is selected randomly without considering its distance from the current location of the user. The distance parameter and how it is incorporated in our mobility model, are discussed in detail in the next section.

3.2.2 Trajectory Selection Criteria

Now that we have settled the positioning of our hotspots, we can describe the way users move around the simulation area and between these hotspots. Consider a user X with the interest profile vector I_X. Also consider a hotspot h with the attraction profile A_h. Similar to the majority of previously proposed mobility models, the movement of a mobile user in our network consists of several consequent trajectories along straight lines. At the end of a trajectory, user X chooses the hotspot h as its next destination with probability $P(X, h)$. In our proposed design of IDMM, P depends on two important factors of human mobility, namely the social attraction and the distance. The more similar h's attraction profile to X's interest profile, the higher the probability. Additionally h's distance to X's current location plays an important role in the probability.

Hotspot Attraction

To measure the similarity of two profiles, in IDMM, we use the dot-product of the two respective vectors. Consider vectors $\vec{a} = [a_1, a_1, \ldots, a_d]$ and $\vec{b} = [b_1, b_2, \ldots, b_d]$.

The dot product of $\vec{a}$ and $\vec{b}$ is defined as follows:

$$\vec{a} \cdot \vec{b} = a_1 \times b_1 + a_2 \times b_2 + \ldots + a_d \times b_d \tag{3.1}$$

Moreover the geometric interpretation of the dot product can be written as follows:

$$\vec{a} \cdot \vec{b} = \|\vec{a}\| \|\vec{b}\| cos(\theta) \tag{3.2}$$

It is clear from the geometric interpretation that the dot product is a good measure of vector similarity. The product is maximized when θ, the angle between the two vectors, is equal to zero, i.e., they are pointing towards the same direction in the n dimensional space.

Distance

When choosing a destination, people are partially affected by their interests and preferred activities. Another important factor in mobility planning is the distance, or how far the target area is located. As an example, consider the case in which two hotspots of equal attraction, say two libraries, are located at different distances from a person who is interested in reading books. Most people tend to choose the closer hotspot as their destination, in order to save time and energy. This is a well studied phenomenon in human mobility. For instance in [51] the authors study the flight length distribution of human mobility patterns. Flights are segments of the movement path that can be approximated by a straight line trajectory. They showed that the lengths of such flights, closely follow a truncated power-law distribution[2].

[2]The power-law distribution of flight lengths, also observed in the animal world, is explained by the scale-free distribution of resources such as food. Another explanation focuses on the Levy-walk's advantage over the Brownian mobility in terms of amount of new area covered by each model given the same amount of time [52]. Interestingly, the distribution was later revisited in a more detailed study and shown to be a Gamma distribution [53].

In Section 2.1.1 we pointed out that recent findings in social network modeling suggest an interesting link between spatial and social relationships. In a nutshell, distance affects the probability of the formation of a social relationship. Kleinberg, et al. take one step further and show through mathematical modeling how this property contributes to one of the more interesting features of human social networks, i.e., its navigability.

As mentioned before, the possibility of decentralized routing based on local information, or navigability, is an essential feature of human social networks. Noticing the lack of navigability in the Watts and Strogatz model[3], Kleinberg proposed an improvement by modifying the randomization process [17]. In his variation, the edges are rewired in such a way that the probability of long-range edges between farther nodes is smaller. More specifically the probability of an edge to a node at distance d, is proportional to d^{-r} where $r \leq 0$. When $r = 0$ Kleinberg's model is exactly the same as that of Watts and Strogatz. As r increases the distribution of long-range edges is skewed more and more towards the vicinity of a node. He proves that for the 2-dimensional case, where d is the Manhattan distance between a pair of nodes, when $r = 2$ the network graph becomes navigable. More importantly, he proved that $r = 2$ is the only value that achieves this property and these results are extendable to any number of dimensions. In other words, starting with a k-dimensional grid, $r = k$ is the only value for which the randomization process results in navigable network models.

To sum up, each trajectory is a cost/benefit problem, i.e., the user wants to move to more attractive places, while keeping the travel length as small as possible. Putting these two factors together, a mobile user will choose a new trajectory according to the following two steps:

[3]See Appendix A

1. **Hotspot**: A hotspot h with attraction profile A_h is chosen as the next destination for user X with probability proportional to $\frac{I_X \cdot A_h}{d(X,h)^\alpha}$, where I_X is the interest profile for X, $d(X,h)$ is the Euclidean distance between the current location of X and h, and the exponent α. The parameter α indicates how fast the probability of moving to a new location drops, as the distance is increased. Exploring the different values for this parameter is out of the scope of this work. However, detailed studies of human mobility traces suggest the range $1 \leq \alpha \leq 2$. The interested reader may refer to the related work listed in Section 3.2.2. Within the scope of this thesis we use $\alpha = 1$.

2. **Coordinates**: A point is uniformly chosen within the selected hotspot at random.

The proposed mobility model captures both the interest and location-induced nature of human mobility. It is important to note that we do not explicitly constrain a user to a certain location or community, unlike previously proposed models such as HCMM (Home-cell Community-based Mobility Model) [36]. For instance, a group of users may belong to a research group besides being a member of a Karate club. Therefore, depending on their interest profile, they may probabilistically move between their lab and the gym, neither of which is necessarily their home location.

In order to properly examine the effects of interest-driven mobility, we need an oblivious model for comparison. Even though RWP is oblivious, it is too simplistic to be directly comparable with IDMM, since they are different from many points of view, e.g., node density, spatial restrictions in mobility, etc. In order to address this issue, we propose the Hotspot Waypoint mobility model, which is very similar to IDMM, except for the fact that attraction profiles have no effect on users' trajectory selection. In other words, Hotspot Waypoint mobility model is a variation of Random Waypoint mobility model in which all waypoints end in our predefined hotspots (certain cells of the simulation area grid).

3.3 Routing Design

As it was briefly mentioned in Section 2.3.2, a class of delay-tolerant routing protocols, known as Spray schemes, consists of two routing phases. The authors of [2] proved Binary Spray to be the optimal strategy, since it would maximize the number of active nodes and minimize the expected time of message delivery. The proof however, is based on the assumption that network nodes have i.i.d. inter-contact times. Under such circumstances all users have equal delivery utilities, therefore the goal is to maximize the number of active users in the shortest amount of time. As a result, an equal distribution of the tokens which leads to a more balanced Spray tree, and maximizes the number of actives nodes (breadth) at any point of time, is the optimal Spray strategy.

The i.i.d. distribution of inter-contact times has been proved to be too simplistic as a model for human mobility in real-world scenarios. Based on this observation, the authors of Spray and Wait modified the second phase and addressed this issue by introducing the Focus mechanism. However, the oblivious Binary Spray strategy would still be used in the first phase. As we shall show later, Binary Spray turns out to be very costly in terms of the delivery overhead, when the mobility is non-i.i.d.

To address this problem, we introduce Weighted Spray routing, a simple yet effective social-aware Spray strategy that helps reduce the overall cost of message delivery when nodes do not follow an i.i.d. mobility model. Consider the case where a node A, currently possessing $n > 1$ tokens of the message m, comes in contact with node B who has not received the message yet. As opposed to Binary Spray where tokens are divided equally, in Weighted Spray, A and B will distribute the tokens among themselves proportional to their likelihood of delivering the message m. Let n_A and n_B represent the number of tokens of the message m in A and B's buffers after the message exchange, ideally:

$$\frac{n_A}{n_B} = \frac{f_m(A)}{f_m(B)}, \tag{3.3}$$

where $f_m(X)$ is our delivery utility function, i.e., the higher the value of the function, the more likely user X is to deliver the message m to its destination. As mentioned before, in this thesis we use the dot product of the user's interest profile and that of the destination node as our utility metric. Thus:

$$f_m(X) = I_X \cdot I_{\mathrm{dest}(m)} \tag{3.4}$$

We also know that $n_A + n_B = n$. Since n_A and n_B represent token counts and have to be natural numbers, the practical values are calculated as follows:

$$n_A = \lceil \frac{f_m(A)}{f_m(A) + f_m(B)} \times n \rceil \tag{3.5}$$

$$n_B = \lfloor \frac{f_m(B)}{f_m(A) + f_m(B)} \times n \rfloor \tag{3.6}$$

It is important to note that this exchange will only take place when $f_m(B) > f_m(A)$. This design choice is made to avoid less effective message replications and reduce the delivery overhead. We are now able to compare Weighted Spraying with Binary Spraying through extensive simulations. The simulation results in the next chapter are obtained by coupling each of these Spraying techniques with the Wait or Focus mechanisms in the second phase.

Another important aspect of the decision making process, is that it does not require network users to have a global knowledge of the network, or to flood the network with update messages of any sort. From user A's point of view, the number of tokens to be transferred to user B at the time of encounter can be computed according to I_A, n, I_B and $I_{\text{dest}(m)}$. The first two pieces of information are already available to user A. I_B can also be obtained through a handshake process before the actual message exchange takes place. Finally, we assume $I_{\text{dest}(m)}$ is embedded in the message, alongside the destination user's network ID. This assumption means that the initiator of a message should be aware of the destination user's interest profile, which is a reasonable assumption in the real world, since the sender of a message often knows the receiver.

Chapter 4

Simulation, Evaluation and Comparisons

Based on the mobile social networking framework introduced in the previous chapter, we conducted a series of simulations and evaluated the performance of our proposed routing protocol. In this chapter we will first introduce the simulation setup and environment. Then by targeting at a specific urban scenario, we make the appropriate choices for our model parameters. Finally, we will present and evaluate the simulation results.

4.1 Simulation Setup

In this section we will introcude our simulation environment and the parameters used through out the simulations.

4.1.1 Simulation Environment

All results that appear in this work are obtained by extensive simulation in the Opportunistic Network Environment (ONE) simulator [54]. This Java-based simulator is specifically intended for simulating Delay-Tolerant Networks and has been frequently cited and improved by the community over the years. In addition to some popular delay-tolerant routing protocols, including Epidemic, Prophet and RAPID, ONE also contains a set of ready-to-use mobility models including RWP. As any other simulator, ONE has some limitations. For instance, physical and MAC layers are not implemented in this simulator. However, within the context of delay-tolerant networking, the overhead and MAC contention would not affect the simulation results noticeably. This is due to the fact that the typical delay for human opportunistic networks can be as high as minutes, hours or days and not nearly as sensitive as ad-hoc networking where fractions of a second matter.

Using this simulator as the platform, we implemented two new modules. The first module is our proposed mobility model, the Interest-Driven Mobility Model (IDMM) and the second one is our proposed routing algorithm, the Weighted Spray Routing, which was implemented by extending the already existing Spray and Wait routing module. To achieve this, we assigned interest profiles and attraction profiles to the users and hotspots, respectively. Both of these modules are available upon request of the interested reader.

4.1.2 Simulation Settings

Scenario

We intend to investigate the efficiency of the proposed routing algorithm, for message delivery in a small-sized urban area. In order to achieve a realistic sense of scale, we consider our city (Victoria, BC, Canada) as a reference. A rough estimate of the map suggests that a square area of 5km×5km would be large enough to cover the major hotspots of the city, e.g., university and colleges, downtown, major shopping centers, etc., each of which spans over an area of 400m×400m on average. This helps us determine the grid size for the Interest-Driven Mobility Model. Our network users are 100 people moving within or between these hotspots, who can potentially store, carry and forward personal messages, news, etc., using their Bluetooth-equipped mobile devices. It is important to note that varying the simulation size, number of users, transmission range, etc. would change affect the duration and the frequecy of contacts which in turn affects the network performance.

Interest Profiles

As we discussed in the previous Chapter, Interest-Driven Mobility Model is mainly based on users' interests and how they are attracted to certain hotspots. Therefore, we need to introduce the category space, prior to discussing the mobility model in detail. The number of dimensions and the distribution of values for user profiles can vary depending on the target scenario. In this thesis, we will use the $\mathcal{U}^a[0,1]$ distribution to generate values for each interest level independently. The resulting vectors are then normalized to their corresponding unity vectors. In Section 3.1 we pointed out that using such a distribution, where a is an integer, leads to a realistic social structure for the network [49]. We also use the 3-dimensional category space, previously mentioned in Section 3.2, and set a to 4[1]. Therefore each interest profile contains three values, each generated by x^4, where x is a uniformly distributed value from $[0,1]$. It is important to note that the number of dimensions, and the distribution

[1]While the model proposed in [49] allows for any integer value, we chose 4 in order to skew the distribution towards smaller values. This is based on the intuition that people tend to be interested in only a small fraction of all the possible categories.

of interests are arbitrary choices specific to this scenario. We have also used a different scenario in our simulations in [55], in which 8 communities were placed around a ring and an 8-dimensional category space was considered with different distributions for the interest values. The simulation results were similar to those presented in this thesis.

It is important to note that in a real world scenario the interest profiles for network users can be obtained in various ways. One approach would be to create, and periodically update, an interest profile based on the content being processed on the mobile device, e.g., the web-browsing history. An alternative would be to adaptively extract user interests based on their mobility and social interactions over time. In [56] authors use machine learning techniques to extract interest profiles for people interacting at a conference, where only a small amount of information about user interests is initially available.

Hotspot Placement

Having settled on a baseline for social attraction, we create the mobility scenario by dividing the simulation area into a grid of cells and selecting a few of them as hotspots. Here, we choose grid cells within a 12×12 grid, according to the layout in Figure 3.1. Table 4.1 shows the attraction profiles for all three types of hotspots in our simulation scenario, given the category space [Studying, Shopping, Dining].

While each of the hotspot in this example, represents one and only one category of activities, our model does not eliminate the possibility of a multi-purpose hotspot, that can have an attraction profile with multiple non-zero weights. In other words, our model allows for any real value between zero and one for the attraction and interest profile values (See our work in [55], in which the attraction values are drawn from a Zipf distribution). The specific choice of zero or one values in this scenario makes each

Hotspot Type	Symbol	Attraction Profile
University	U	[1, 0, 0]
Shopping Center	S	[0, 1, 0]
Downtown Area	D	[0, 0, 1]

Table 4.1: Hotspot Attraction Profiles.

hotspot very distinct allowing for an effective evaluation of Weighted Spray Routing.

It is important to note that the simulation area and the community locations are taken from the real world scenario we discussed earlier, i.e., the map of Victoria. Once the network users are placed in the simulation area, they will move towards these hotspots according to the IDMM mobility model. Since the mobile users are initially placed uniformly at random, we allow a warm-up period of 2 hours for the mobility model to stabilize in simulation. According to our calculations, considering the minimum movement speed, the maximum travel distances and the maximum waiting time, 2 hours should be enough time to allow for three to four travels for every network user. We also verified visually that the network users achieve a stable distribution after this 2 hour period.

Mobility Parameters

To create a convincing scenario we took other important features of realistic human mobility into account. First, we distinguish between intra and inter-hotspot mobility, in the sense that the movement speed for these two scenarios is uniformly distributed around the average walking and driving speeds, respectively. That is to say, people tend to drive a car or take the bus when it comes to moving around the city, and walk when the destination is within the same hotspot. Secondly, at the end of each waypoint, a mobile user pauses for a uniformly distributed amount of time before starting the next movement. These gaps, also known as “Pause Times” are intended to imitate the involvement of the user in a particular task, or the small pause before changing the direction and choosing a new waypoint.

Traffic Pattern

During a period of 7 days, 2,800 messages are initiated for randomly selected sources and destinations. That is to say, an average of 4 messages are created by every user on a daily basis. Message creation times are evenly distributed within the simulation time, with minor uniform variations to avoid unwanted repetitive artifacts[2]. All messages are of size 80 kB, which is a rough estimate of the size of an email message alongside a relatively small attachment. Finally, the Time-To-Live (TTL) for all messages is set to 6 hours to allow for a reasonable number of successful deliveries, given the harsh network conditions of our scenario, i.e., a network of only 100 users, with 10 m of transmission range and the transmission speed of 100 kBps. Moreover, 6 hours is an acceptable upper bound for the delivery delay in many non-emergency applications. As we will show later in the simulation results section, despite the 6 hour TTL, even the Epidemic routing algorithm has difficulty delivering roughly 30% of the messages to their destinations.

Networking Devices

Due to the availability of the Bluetooth technology in most portable devices such as cellphones and tablets, we use it as the basis of our network communication specifications throughout the simulation scenario. According to the specifications, an average communication range of 10 m and a transmission speed of 100 kBps are reasonable choices. We also assign 1 GB of message buffer memory to each device. We understand that buffer occupancy is an important measure of efficiency when it

[2] The initiation time for the n^{th} message is $n \times 216s + X$, where the offset variable X is drawn from $\mathcal{U}[-60, 60]s$

comes to routing in small mobile devices. However we set the buffer size to a high enough value, such that no buffer overflows would happen, given our traffic specifications. By avoiding buffer overflows, we are able to focus on the total number of transmissions and compare the different routing strategies in isolation, without any side effects caused by a specific buffer management strategy[3]. Further details about the simulation parameters are provided in Table 4.2.

Category	Parameter	Description
General	Simulation Area	5000×5000 m^2
	Number of Nodes	100 mobile
	Duration	7 days
Mobility Model	Warm-up Period	2 hours
	Walking Speed	Uniform $[.5, 1.5]$ m/s
	Driving Speed	Uniform $[8, 14]$ m/s
	Grid Size	12×12
	Waiting Time	Uniform $[1, 1800]$ s
Network	Transmission Range	10 m
	Transmission Speed	100 kBps
	Storage Size	1 GB
Traffic	Message Size	80 kB
	Message Initiation Rate	400 per day (whole network)
	Message TTL	6 hours

Table 4.2: Simulation Parameters.

Before discussing the simulation results, we need to comment on our choice of parameters. While we have attempted to choose realistic values for our simulation parameters, from traffic load to network capacity, a curious reader might wonder how would the simulation outcome differ if these conditions were altered. We have attempted to address this concern to the best of our knowledge, and within the scope and limitations of this thesis.

First, the values for our simulation parameters are chosen and justified based on a

[3]Several buffer management strategies for Delay Tolerant Networks have been proposed in the literature. See [57] for an example.

realistic scenario, e.g., the network capacity is dictated by the practical specifications of the Bluetooth technology together with the typical storage capacity of an everyday mobile device. Secondly, we have attempted to cover various scenarios by changing the values for some of the parameters, to see if they have any significance in our final results and conclusions. For instance, an examination of a scenario with different hotspot placement and higher number of dimensions for the category space, led to similar results and was excluded from this work [55]. Our final argument is based on the simulation results that follow. They show that our proposed routing scheme outperforms others, in terms of efficiency, i.e., achieving a similar delivery performance at a lower cost. More specifically, our scheme achieves a similar delivery ratio and delay while it consumes less of the network resources such as the total number of transmissions and the average buffer occupancy. Therefore we can argue that a scenario with a higher traffic load or a decreased network capacity, would only help bring out the advantages of our scheme under more critical conditions.

To the best of our knowledge, there are no publicly available human mobility datasets that also provide rich information about the personal interests of the network users. The Reality Mining [58] and Infocom [59] datasets, are the only instances that contain any information about the users' profiles. However they are only in the form of interest tags and lack enough depth (interest values) and breadth (number of dimensions) for the purpose of our study.

It is also important to note that we do not inform the network about the successful delivery of a message. As a result network nodes may store/carry/forward a message that has already been delivered. Due to the unreliable nature of Delay-Tolerant Networks, we chose not to propagate control messages across the network for every delivery to avoid further replication or forwarding of a message.

4.2 Simulation Results and Performance Evaluation

Now that we have determined the simulation scenario and settings, in this section, we will present and evaluate the simulation results. Starting from the mobility model, we will first discuss the main differences between IDMM and HWP, and show how they affect the performance of the Epidemic routing protocol. Then, by using the IDMM mobility model as the more realistic of the two, we will demonstrate how Weighted Spray techniques outperform their binary counterparts. Before presenting these results, it is important to explain what we mean by the “performance” of a routing protocol.

All data points throughout this Chapter are obtained by averaging over 10 simulation runs, unless stated otherwise. The error bars indicate the standard deviation. In many cases the standard deviation was too small to include, therefore no error bars were plotted.

4.2.1 Performance Metrics

In this thesis four quantitative measures are used to evaluate the performance of opportunistic routing protocols.

1. **Delivery Ratio:** The number of unique messages delivered, divided by the total number of messages initiated. The higher the better.

2. **Delivery Delay:** The elapsed time between message initiation and its successful delivery. The lower the better. However within the context of Delay-Tolerant Networking this performance metric has a lower priority in a trade off against the other performance metric, the delivery ratio.

3. **Buffer Occupancy:** The average number of messages in a user's buffer at any moment. A routing algorithm with a lower average buffer occupancy, uses less of the network memory resources.

4. **Delivery Overhead:** Used as a measure of message delivery cost in this work, this metric is explained in detail later in Section 4.2.3.

4.2.2 IDMM vs. HWP

In this section we present a series of quantitative comparisons between the following two mobility models:

1. **Hotspot Waypoint (HWP):** A modified version of RWP which is a widely used mobility model due to its simplicity [28]. In this modification, all trajectories end in specific regions of the simulation area, predefined as hotspots.

2. **Interest-Driven Mobility Model (IDMM):** Our proposed interest/location driven mobility model as described in Section 3.2 where the inter-contact time distributions are neither identical nor independent.

We first show how the contact patterns are essentially different for each of these mobility models. Then we illustrate how these differences affect the performance of existing routing protocols.

Distribution of the Total Number of Encounters

Figure 4.1 (a) depicts the heterogeneity of contacts in IDMM. In this figure we have plotted the number of encounters, within a 7 day period of IDMM mobility for a network of 100 mobile users (the x axis is user ID), averaged through 10 runs of simulation. In this plot, the number of unique encounters is indicated as the bottom

Statistical Measure	IDMM	HWP
Average	473.5	557.3
Standard Deviation	153.7	11.3

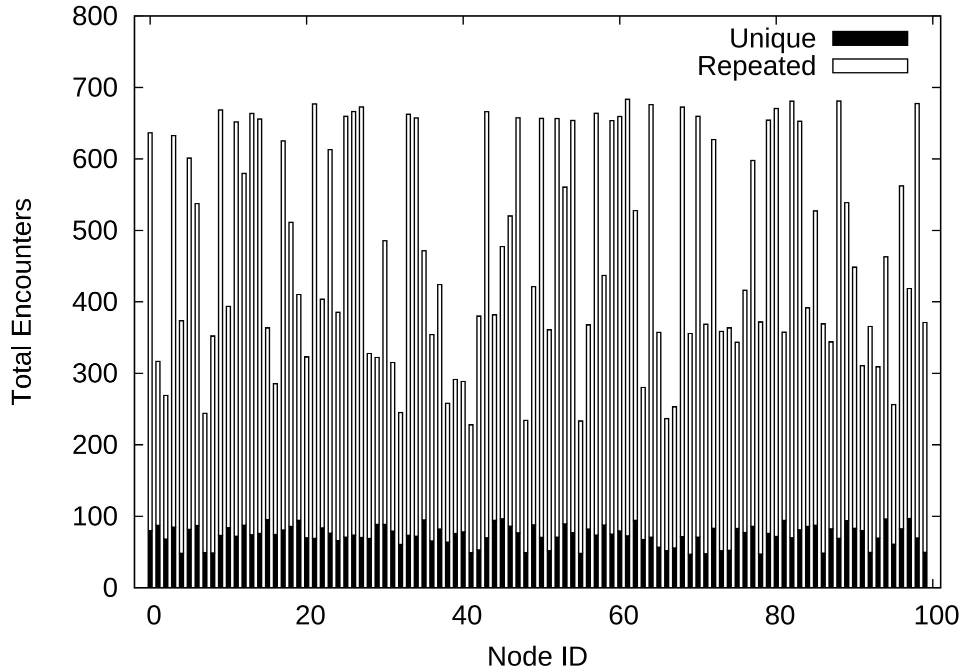
Table 4.3: Total Number Encounters in IDMM and HWP.

portion of every bar colored in black. The same type of data is plotted for the Hotspot Waypoint mobility model in Figure 4.1 (b). As the distributions suggest, in IDMM, the total number of encounters ranges from 228 to 683.5, while the values are more concentrated in HWP and range from 531.4 to 580.8. In Table 4.3 we have provided the mean and standard deviation values for the total number of encounters across the network users, for both of these mobility models. As expected, the data clearly shows that movement patterns in IDMM have a much higher variety, when compared with the HWP mobility model, where individuals' interests are not taken into account.

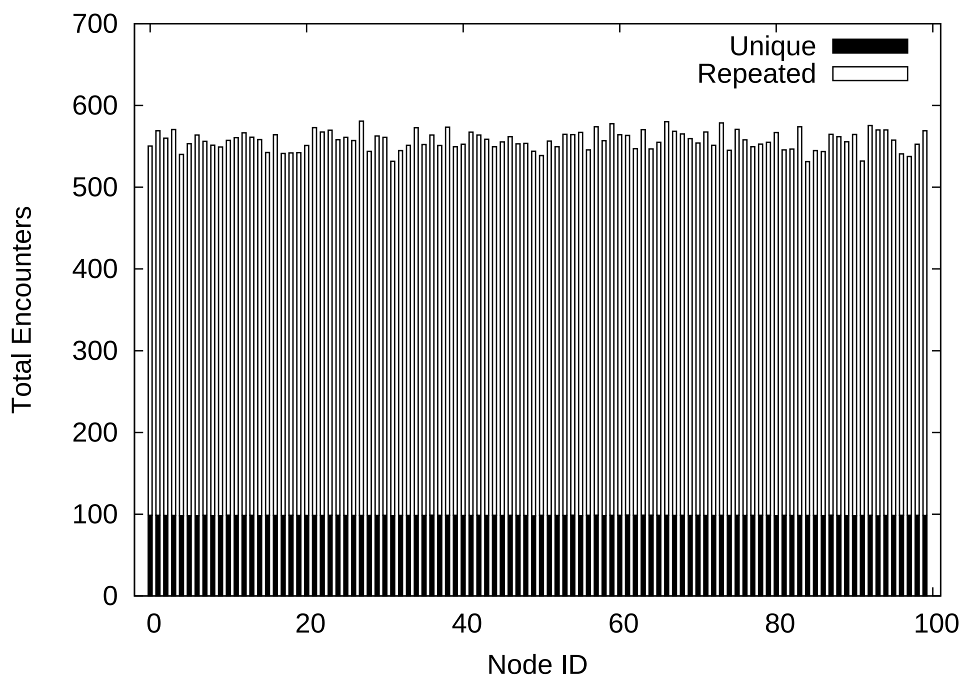
Aside from the higher deviation value, there exists an essential difference between the encounter count deviation in IDMM and that of HWP. In IDMM mobility, some users are inherently more social than others due to their interest profile characteristics. For instance, a student who in addition to spending time on campus also enjoys dining out (studying and dining activities), is more likely to encounter a larger set of people, when compared with a student who almost exclusively studies and spends the majority of her time on campus (studying activity). Therefore we see a larger deviation in contact patterns, while the deviation in HWP are smaller and can be purely associated with the randomness in mobility.

Correlation Between Frequency of Contacts and Profile Similarities

Another evidence for the IDMM mobility model being non-i.i.d. is provided in Figures 4.2 and 4.3. In this experiment we allowed the network users to move around the simulation area for 7 days according to the IDMM mobility model. The history



(a) IDMM



(b) HWP

Figure 4.1: Number of Unique and Repeated Encounters

of pairwise contacts were then logged for examination. Every point in this plot represents a pair of mobile users. For each pair, their total number of contacts during the simulation is plotted against their profile similarity, i.e., the dot product value. As the figure suggests there is a strong positive correlation between the two variables, meaning that, the more similar the interest profiles, the higher number of overall contacts. However this correlation does not hold for all instances as indicated by the bottom right portion of the plot. In these cases pairs of users have high interest similarities yet very few number of contacts. This is due to the fact that, distance plays a role in the way users move around the environment. That is to say, two users who have similar interests may not meet very often, due to being far from each other. Additionally, due to the very low transmission range of the devices, two users at the same hotspot have a high chance of not encountering each other. The exact value of the correlation was calculated to be 0.767. As Figure 4.3 suggests a similar correlation does not exist when users move around following the HWP mobility model (correlation = 0.056).

Optimal Route Characteristics

We now compare the two mobility models by analyzing the topology of their respective temporal connectivity graphs. More specifically, we are interested in the characteristics of the average shortest paths in each scheme. In order to do so, we eliminate the bandwidth limitation and use the Epidemic routing. As we discussed before, in the absence of bandwidth limitation, Epidemic routing delivers the messages via the shortest possible paths. We then measure the average characteristics of such optimal paths, the results of which are summarized in Table 4.4.

The first observation from Table 4.4 is that the average length of the shortest path in terms of hops, is very small for both scenarios. This is a quite obvious for HWP,

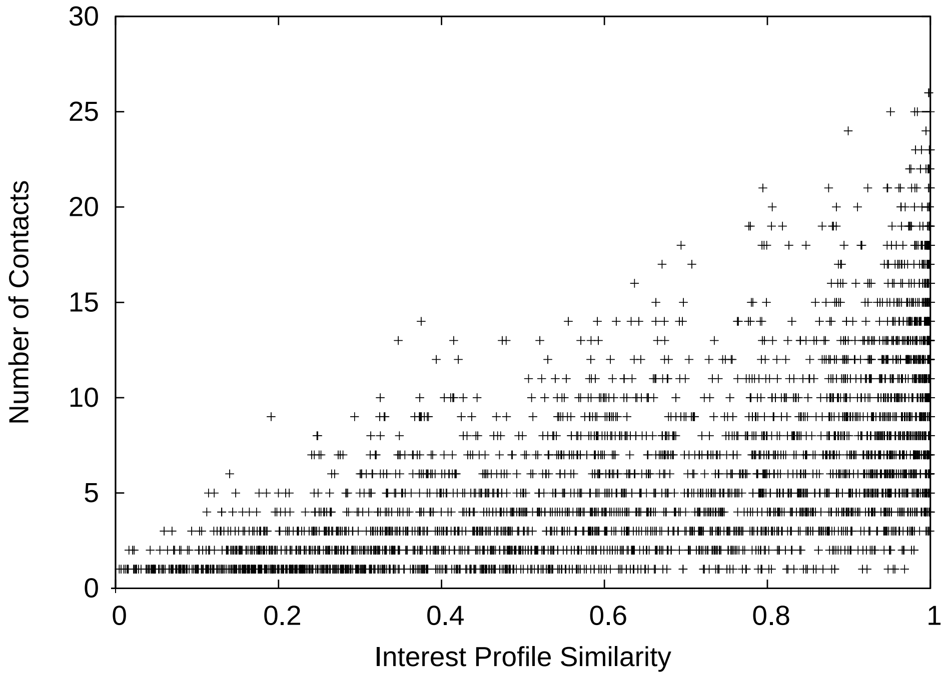


Figure 4.2: Number of Contacts vs. Profile Similarities in IDMM.

Performance Metric	HWP	IDMM
Delivery Ratio	76.0	66.0
Hop-count	3.0	3.3
Overhead Ratio	49.1	59.6

Table 4.4: Optimal Path Characteristics in IDMM and HWP.

since its respective temporal graph is very close to a completely unstructured randomized graph[4]. However this is an interesting property for IDMM, which demonstrates how the model has successfully captured the small-world property of the mobile social networks. Nevertheless, the average length of the shortest path is slightly higher for the IDMM model, which is an expected aspect of its structured temporal contact graph. That is to say, an isolated user has no other way of sending a message to someone outside of her community, other than involving a third-party user who trav-

[4]This is true to some extent. Since in the HWP contact graph, two nodes who have encountered a common node about the same point in time, are more likely to encounter each other, when compared with two randomly chosen nodes. This is not the case for a randomized contact graph.

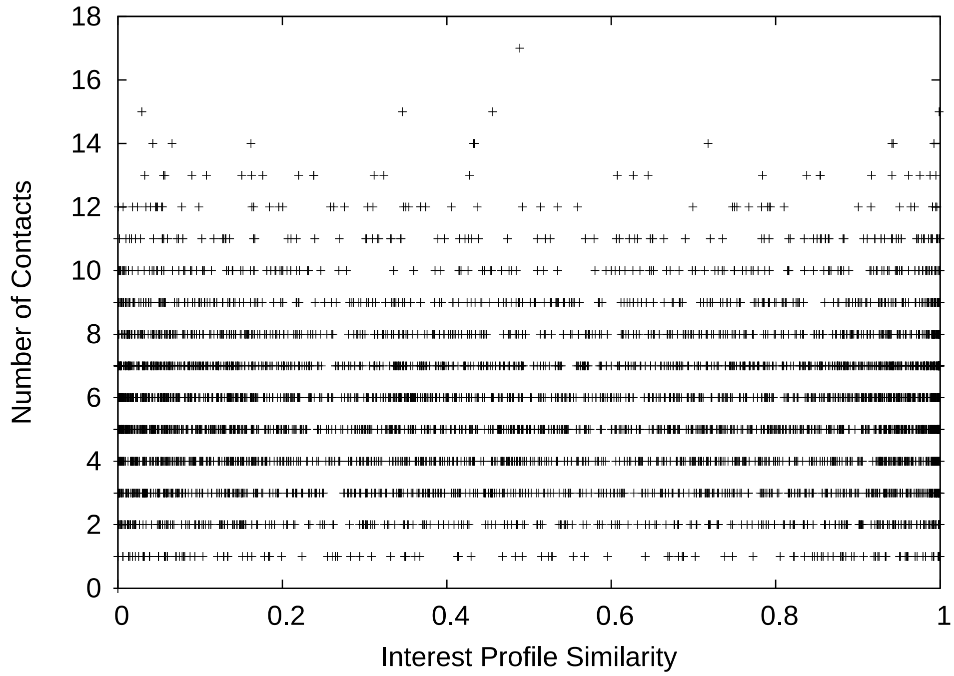


Figure 4.3: Number of Contacts vs. Profile Similarities in HWP.

els between the two communities. This is not the case in HWP since every user has the possibility of moving to any other community (hotspot) regardless of its nature.

Table 4.4 also suggests that the delivery ratio of the Epidemic routing is lower when the IDMM mobility model is in effect. This is easy to explain, based on our previous discussion on the average length of the shortest possible path. Since the shortest paths are longer in IDMM's temporal graph, more messages reach their TTL before delivery, hence the lower delivery ratio when compared with HWP. Moreover, the fact that the delivery overhead is higher for IDMM, suggests that the oblivious replication of messages can be more costly, when the mobility is not i.i.d. This is an important observation since it demonstrates the potential for improving the oblivious Spraying techniques such as Binary Spray. In the following sections, we will show how our proposed context-aware Spraying technique successfully reduces this delivery cost.

4.2.3 Weighted Spray Routing

In the previous section we demonstrated the high overhead ratio of oblivious routing schemes such as the Epidemic routing, when the mobility model of network users is non-i.i.d (Table 4.4). We will now show how Binary Spraying techniques also suffer from the same problem. Finally, we will show how the Weighted Spray scheme helps alleviate this problem, by studying its performance from various points of view. We compare the following four routing algorithms, as all possible combinations of Binary or Weighted Spraying coupled with Wait or Focus at the second phase of delivery:

1. **BSW**: Binary Spray and Wait
2. **WSW**: Weighted Spray and Wait
3. **BSF**: Binary Spray and Focus
4. **WSF**: Weighted Spray and Focus

We use the Interest-Driven Mobility Model based on the map of Victoria (Figure 3.1), for all simulation results that follow.

Message Delivery Ratio

Figure 4.4 shows the average delivery ratio of each routing scheme when L, the initial number of copies, is varied from 1 to 20. As L is increased, the Spray routing becomes more and more similar to the Epidemic routing. We would like to emphasize that the authors of [2] suggest roughly 5% to 15% of the network population as the optimal number of initial copies, which is covered by this interval.

The results for the IDMM mobility model suggest that all four Spray routing schemes have a better chance of delivery, when the initial number of copies is increased. Moreover, both routing algorithms coupled with Focus outperform their

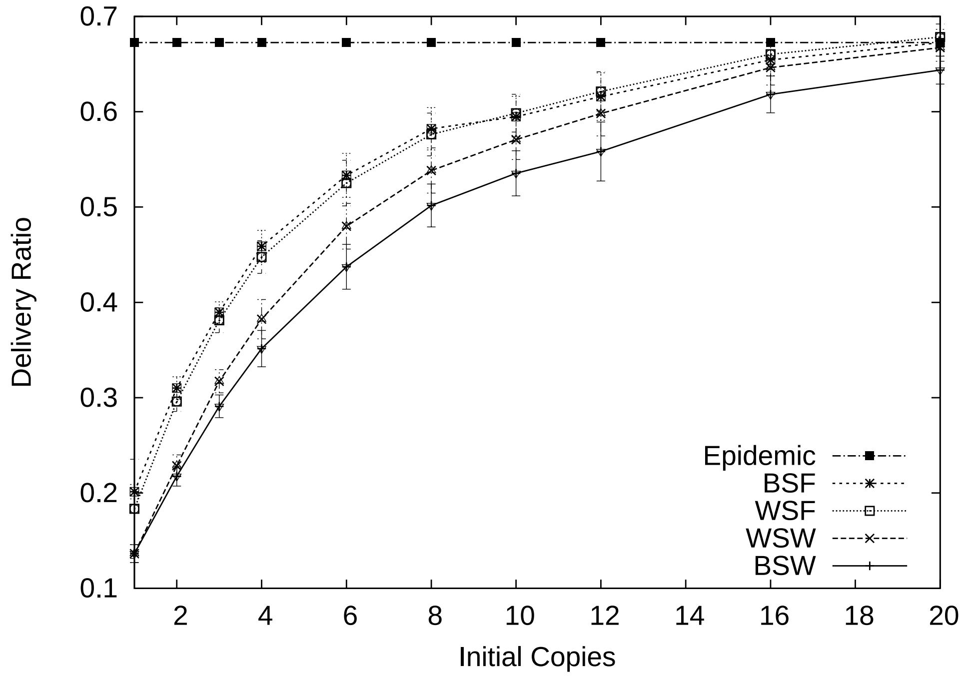


Figure 4.4: Delivery Ratio vs. Number of Initial Copies.

counterparts coupled with Wait. Interestingly, the Weighted Spray technique seems to improve the routing performance when coupled with Wait. But when Focus is in use, the delivery ratio is almost unchanged. To explain these results, we need to recall that the Weighted Spray technique can act as a double-edged sword. On one hand it skews the distribution of messages towards the social communities to which the receiver of the messages belongs, potentially improving the delivery ratio. On the other hand the Spray tree is more unbalanced, resulting in a lower tree breadth at any point in time. This is due to the fact that in Weighted Spraying, replications do not happen as rapid as they do in Binary Spraying. As opposed to the Binary scheme in which the purpose is to Spray the tokens as fast as possible, the Weighted scheme keeps the tokens clumped up in the buffer of network nodes who are more similar to the destination node. The fact that Weighted Spray takes a longer time to finish, could potentially harm the performance of the weighted scheme, when compared with the binary scheme. This trade-off will be discussed in the upcoming Section 4.2.3.

Message Delivery Delay

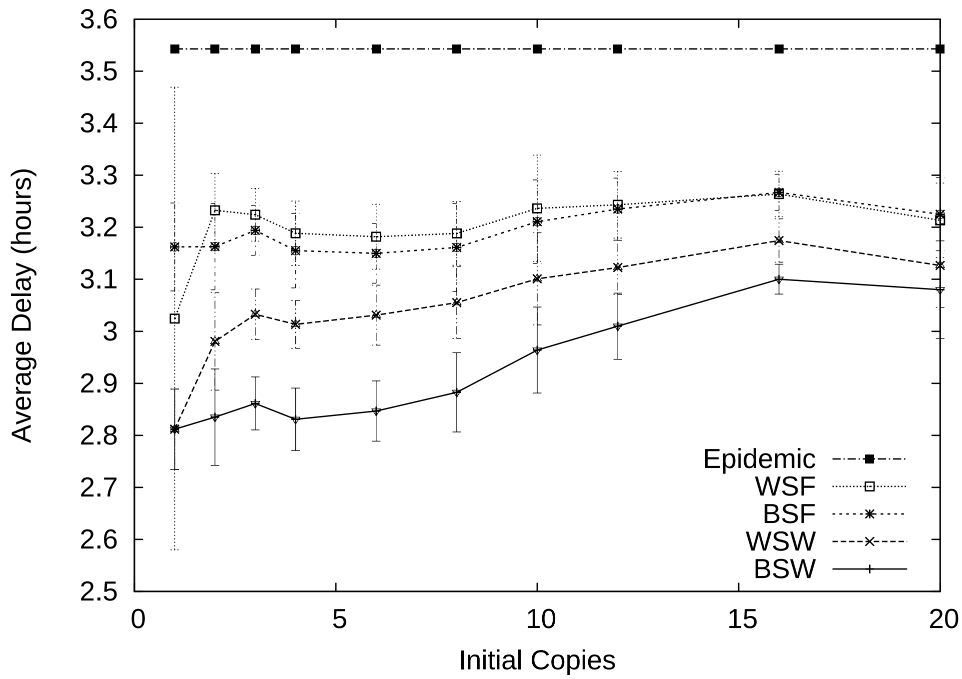


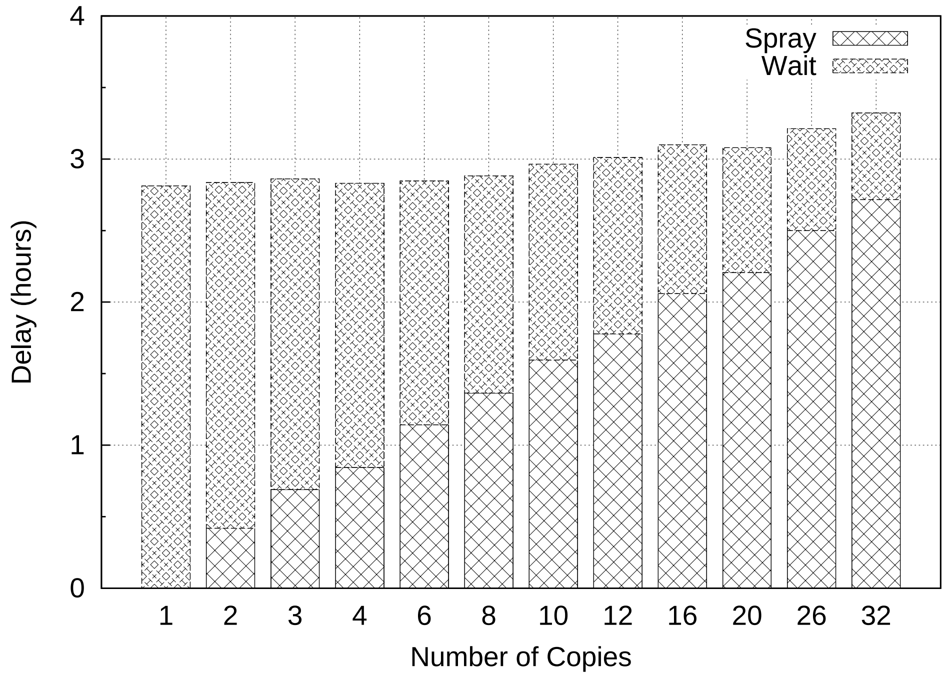
Figure 4.5: Delivery Delay vs. Number of Initial Copies.

In Figure 4.5 the average delivery delay has been plotted with respect to L. As the initial number of copies is increased, one can observe an overall increase in the delivery delay of all four Spray routing algorithms. This is due to the fact that with a higher number of tokens, more messages are delivered successfully, hence the average delivery delay is affected by these new instances. The same reasoning applies to Epidemic routing's average delivery delay being the highest of all five algorithms. However, the differences among the four Spray routing variations are quite small and insignificant. Figure 4.5 also verifies our hypothesis about the trade-off introduced by the Weighed Spray technique. Each Weighted Spray algorithm suffers from a slightly higher delay, when compared with its Binary Spray counterpart. To better understand this effect we consider the breakdown of the delivery delay into two parts. That is we consider the delivery path for every successful delivery. We then keep track of the time spent in each phase of the delivery, namely Spray (Binary/Weighted) and delivery (Wait/Focus).

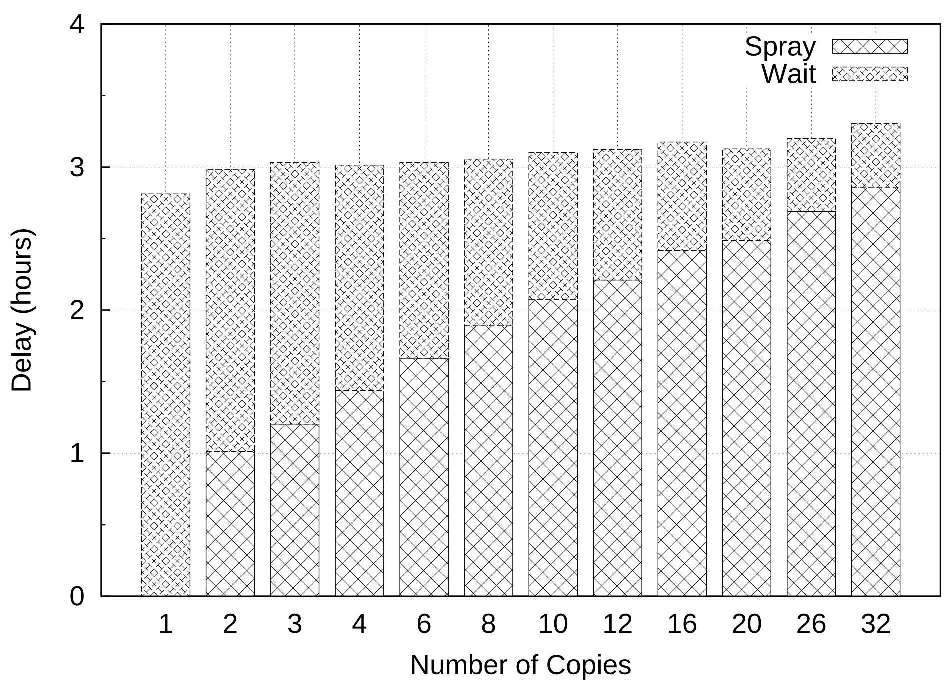
In Figures 4.6 and 4.7 we can observe what portion of the overall delivery delay each phase of the routing algorithm is responsible for. As the initial number of copies is increased the Spray phase takes larger and larger portions of the overall delivery delay. This is very intuitive since it takes longer and longer for the messages to run out of tokens, and according to the protocol the second phase of delivery (wait or focus) for a copy of the message, starts when it is left with only one token.

It is also interesting to note the differences between weighted and binary schemes. Here we take the BSF and WSF pair as the basis for our discussion (Figure 4.7), however it is important to keep in mind that the same arguments apply to the BSW and WSW pair. As we briefly pointed out previously, due to the fewer number of active nodes, the Spray phase takes a longer time when Weighted Spray is in use. On the other hand, since Weighted Spray directs more copies towards the target social community of the destination, the users who start the delivery phase, are much more likely to deliver the message to its final destination in a shorter amount of time. Therefore, as confirmed by the figure, the delay associated with the focus phase ends up being shorter.

Even though our weighted scheme seems to suffer from a slightly higher overall delivery delay w.r.t. the initial number of copies, we will show later that this small gap in delivery delay leads to a significant trade-off in terms of the overall cost of the Spray schemes.

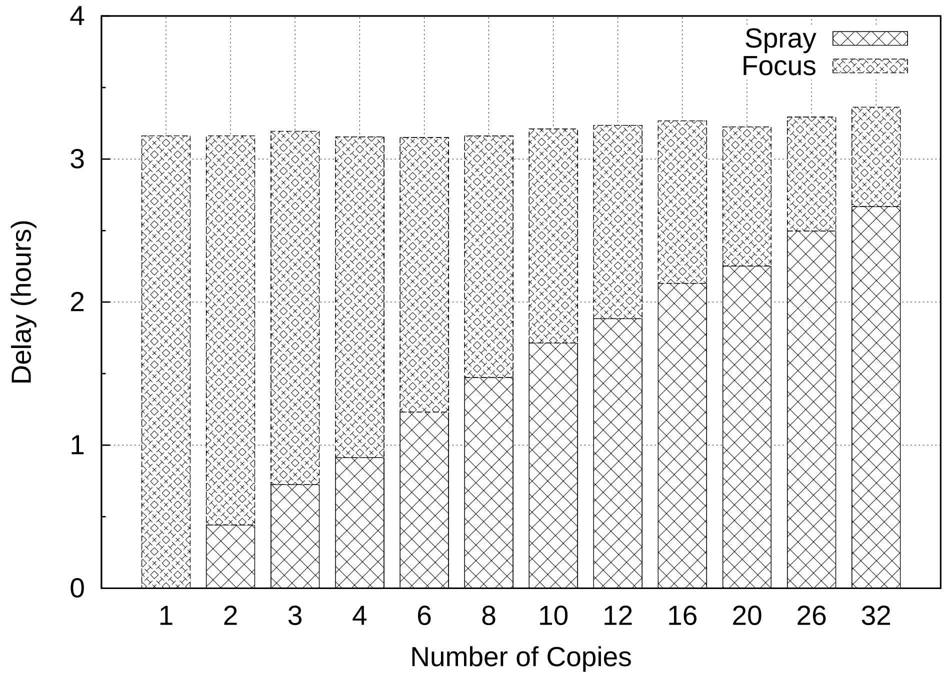


(a) BSW

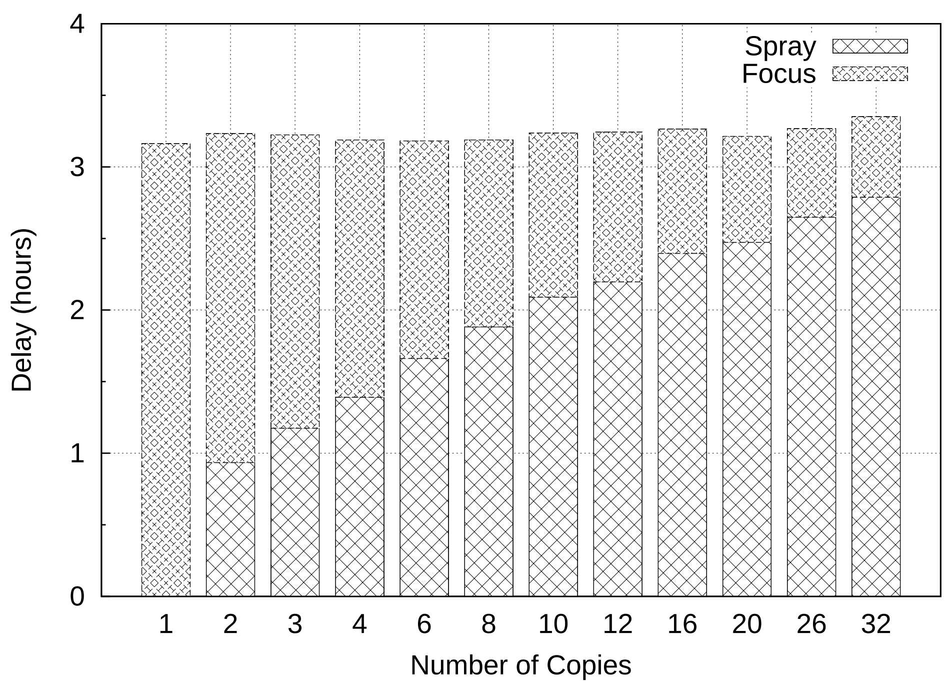


(b) WSW

Figure 4.6: Delivery Delay for Spray and Delivery Phases. (Wait)



(a) BSF



(b) WSF

Figure 4.7: Delivery Delay for Spray and Delivery Phases. (Focus)

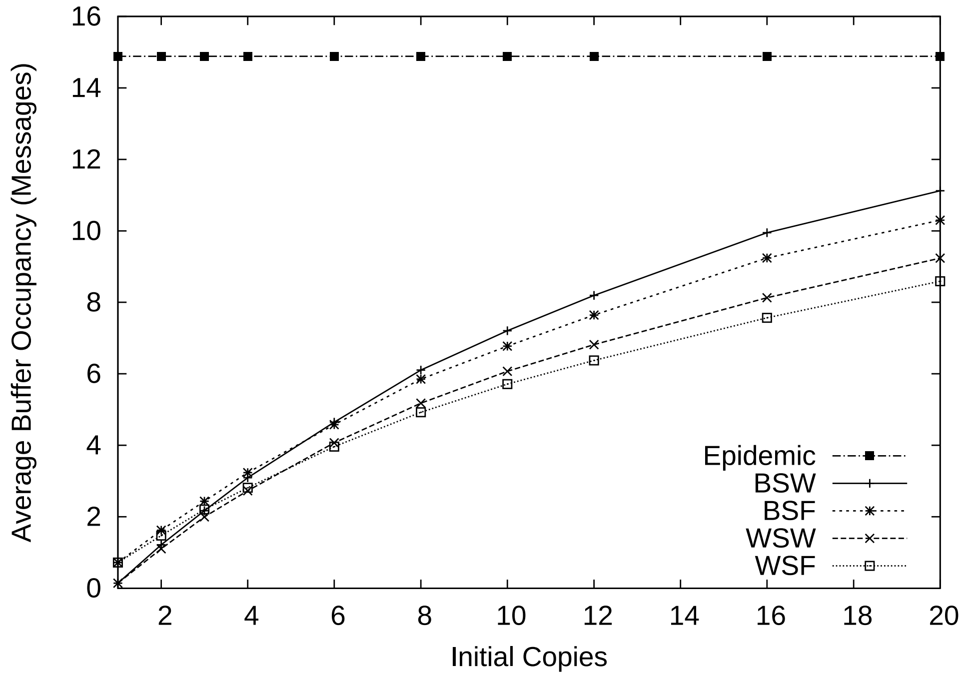


Figure 4.8: Average Buffer Occupancy vs. the Number of Initial Copies.

Buffer Occupancy

Buffer Occupancy was defined in Section 4.2.1 as an important cost factor when comparing routing strategies. In Figure 4.8 the average buffer occupancy is plotted against the initial number of copies (L). As L is increased, the buffer occupancy is expected to increase for all four Spray routing algorithms, due to the higher number of replications. However, the Weighted Spraying techniques seem to be using less of the network's memory capacity, when compared with their Binary counterparts. This is a direct result of the fewer number of active users, which was explained in the previous section.

Message Delivery Overhead

The total number of transmissions is a crucial measure of the delivery cost in delay-tolerant networks. Message delivery overhead is a performance metric that measures

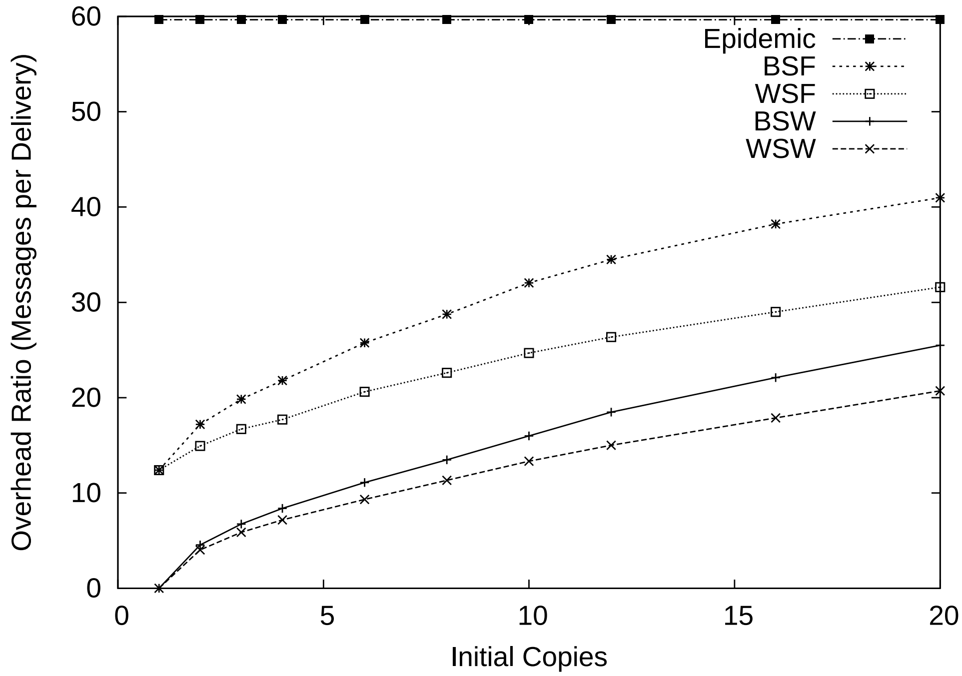


Figure 4.9: Message Delivery Overhead vs. Number of Initial Copies.

this cost in a meaningful way, i.e., normalized over the number of delivered messages [60]:

$$\mathrm{MDO} = \frac{\mathrm{N_{transmitted}} - \mathrm{N_{delivered}}}{\mathrm{N_{delivered}}} \tag{4.1}$$

In Figure 4.9, MDO is plotted against the initial number of copies for all four possible combinations of Binary/Weighted Spray and Wait/Focus, in addition to the Epidemic routing as a constant upper bound. From this point of view, both weighted schemes are more efficient than their binary counterparts. This is specially true for Weighted Spray and Focus, since active copies are distributed towards the target community and fewer transmissions are required in the focus phase. In Binary Spray and Focus (BSF) however, messages are sprayed as fast as possible, assuming the i.i.d. inter-contact time distribution for all network nodes, throughout parts of the network without considering their social distances to the destination node. As a result many focus sequences are quickly initiated in parallel, most of which will not lead to a successful delivery, but increasing the delivery overhead.

Delivery Ratio and Delay Revisited

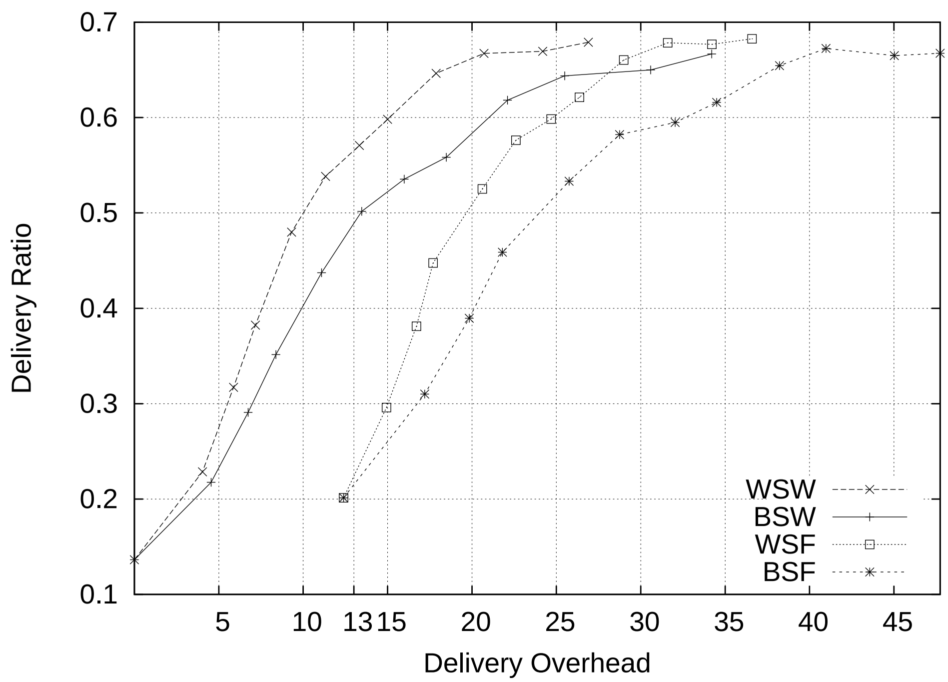


Figure 4.10: Delivery Ratio vs. Message Delivery Overhead.

An important take-away message from Figure 4.9 is that *the initial number of copies is not an ideal measure of the imposed overall cost to a delay-tolerant network as a whole.* Based on this observation we revisit the four routing schemes and compare their performance with respect to the actual cost of extra transmissions they inflict upon the network, i.e. the overhead ratio.

Figure 4.10 illustrates the advantage of the Weighted Spray schemes, i.e., for both Weighted schemes the delivery ratio is higher when compared to their respective Binary Spray schemes. For instance if one is willing to *pay* the cost of 13 extra

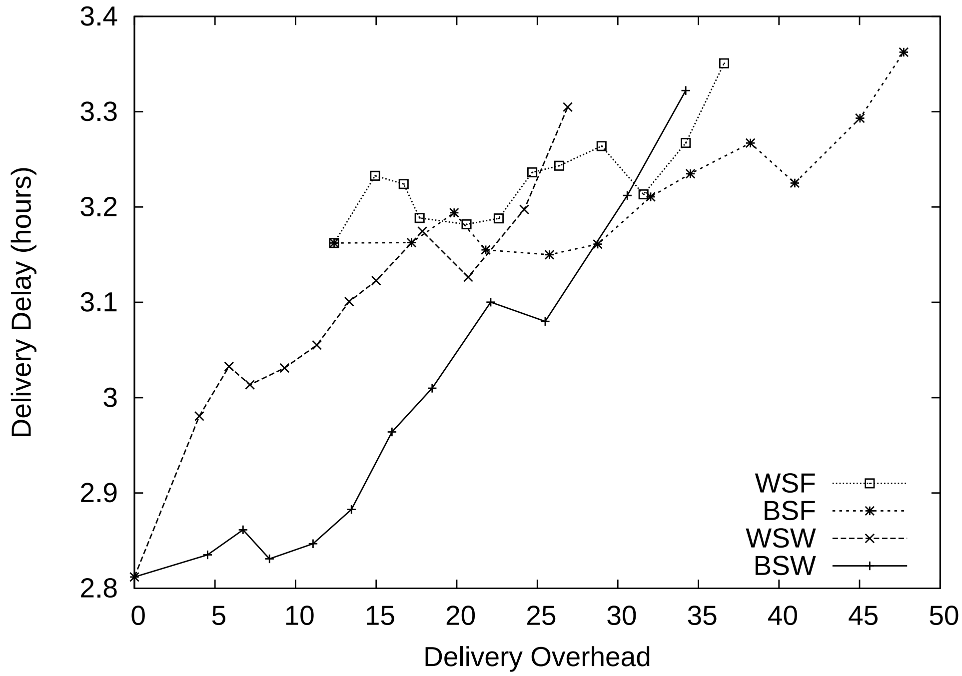


Figure 4.11: Delivery Delay vs. Message Delivery Overhead.

transmissions per delivery (overhead = 13), they could either use Binary Spray and Focus with 8 initial copies and achieve a delivery ratio of around 0.5, or use Weighted Spray and Focus using 10 initial copies and achieve a higher delivery ratio of 0.57.

Finally, as Figure 4.11 suggests the delivery delay of WSF and BSF schemes are very close, while WSW is slightly slower than BSW. However these differences are very small when compared with the overall delivery delay of these Delay-Tolerant Routing algorithms. That is to say within the context of Delay-Tolerant Networking an extra delay of around 12 minutes (worst case) on top of the 3 hour delay, is an acceptable trade off considering the performance gain in delivery ratio.

In this Chapter, we showed how our proposed Weighted Spraying technique improves the performance of Spray routing algorithms. We showed that our scheme has a higher delivery cost in terms of both buffer occupancy and the delivery overhead. We further demonstrated that with respect to the inflicted overhead to the network, our scheme outperforms the Binary scheme in delivery ratio, with little or no extra overall delay.

Chapter 5

Conclusions and Further Discussions

5.1 Conclusions

In this thesis, we explored the personal interest in intermittently connected wireless mobile social networks. By identifying the basic elements of human mobility, we proposed IDMM, a mobility model that takes into account both the individual interests of each user, and the role of social hotspots. By studying the contact patterns of the users, we confirmed that users' movement patterns in IDMM are neither identical nor independent, which conforms to the findings of human mobility research reviewed in Chapter 2.

Using the IDMM mobility model, we evaluated the performance of previously proposed Spray schemes and showed that Binary Spraying suffers from a relatively high message delivery overhead, in presence of non-i.i.d. mobility. To address this issue, we proposed Weighted Spray to reduce the observed delivery overhead of Binary Spray. According to our results, while the Weighted Spray scheme does not inflict a significant increase in the overall delivery delay, it leads to a more efficient use of users memory resources. Finally, and most importantly, we showed that Weighted Spray is able to outperform the Binary scheme, in terms of the delivery ratio.

5.2 Future Work

5.2.1 Adaptive Behavior

In Section 4.2.3 we discussed the trade-off between Binary and Weighted Spraying schemes, in terms of their respective delivery delays. On one hand, Weighted Spraying helps target a specific set of users, who are more likely to contact the destination. On the other hand, the unbalanced distribution of tokens, prolongs the Spraying process. A possible improvement would be to adjust the Spraying strategy, based on the remaining TTL of each message. That is to say, the new Adaptive Spray strategy must be very sensitive to the delivery utility of an encountered user, when a message has a long time left before expiry. However as the remaining TTL gets shorter, the algorithm becomes less sensitive to the utility value, and transmits the message regardless of the relay node's delivery utility. The aggressive forwarding is for the sake of increasing the chances of delivery before the message's TTL runs out.

5.2.2 Online Stopping Algorithms

Following the idea of Adaptive Spraying, one can improve the utility-based forwarding problem in Delay Tolerant Networks. As we discussed in Section 2.3.2, Focus, is a single-copy utility-based forwarding algorithm in which, the message is forwarded to another user, only if the other user has a higher delivery utility. The remaining TTL can once again be incorporated in the decision making process. In this case however, due to its relative simplicity when compared with the Spraying problem, we can use the concept of online stopping problems to mathematically model the problem at hand, and ultimately solve it mathematically. An online stopping problem consists of a series of observations, and a series of associated rewards. The observer can either stop on an observation and be rewarded accordingly, or reject the current observation and move on to the next observation. The goal is for the observer to maximize her reward. Different variations of this problem have been solved by means of probabilistic methods. One variation is particularly interesting for our purpose, in which rejecting an observation introduces a small cost, decreasing the overall reward.

Going back to the problem of single-copy utility-based forwarding, we will now create a bridge between these two problems. A network user carrying a single copy of a message can be regarded as the observer. The observations are the candidate relay nodes he or she encounters over time. The reward associated with each observation is the delivery utility of the relay node. Finally, the cost associated with passing an observation, is the amount of an elapsed time until the next encounter, which increases the overall delivery delay. The solution to this stopping problem, would indicate the encounter in which the observer must forward the message to another peer, in order to maximize the chances of a successful delivery. More details on the problem formulation and further discussions are provided in [61].

5.2.3 Stationary Network Elements at Hotspots

In this thesis, the notion of a social hotspot is currently used for the sole purpose of designing a more realistic mobility model. It would be interesting to look at the possibility of equipping these hotspots with storage or network access points, enabling them to act as stationary network elements. This modification can improve the performance of opportunistic routing protocols in different ways. For instance, by providing a large amount of storage space, they can provide a more reliable way of communication guaranteeing that a certain message will stay in a social hotspot, waiting for the receiver to collect it. A real-life example of this communication paradigm is leaving a note on the note board of a coffeehouse, where you expect the receiver to eventually go to. Without having the note board as a reliable stationary unit one would have to leave the message to an intermediate person who may or may not stay at the hotspot by the time the final receiver gets there. Furthermore, the access points can communicate with each other, by means of some infrastructure connectivity. The improvement caused by this partial infrastructure-based connectivity in mobile social networks is potentially an interested topic of study.

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Appendix A

The Watts Strogatz Model

Proposed by Watts et al., this graph model exhibits many essential structural features of the human social networks [14]. All network nodes are placed around a ring. To create the edges of the graph, we start from a completely ordered structure, in which every node is connected to its K closest neighbors. For instance when $K = 2$, every node is connected to its left and right neighbors creating a complete ring. As the value of k is increased the clustering coefficient of the network increases. Even though the resultant graphs have high clustering coefficients, the average path lengths are still in the order of $O(n)$ where n is the number of nodes in the network. To address this issue, Watts et al. propose a randomization process, in which every edge of the graph is "rewired" with probability p (avoiding duplicate edges and self-loops). These edges are also referred to as "long-range edges" in the social networks literature.