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Mobile Peer-to-Peer Data Dissemination over Opportunistic Wireless Networks

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CONTENTS

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ABSTRACT

This thesis investigates mobile peer-to-peer data dissemination over opportunistic wireless networks for providing ubiquitous content dissemination beyond Infrastructure networks. As user-generated content sharing and online video service becomes popular, current wireless Internet architecture can become saturated and overloaded with large increase in the volume of user-generated traffic, not only for its radio access network, but also for core network on the Internet. Mobile peer-to-peer data dissemination is an alternative data distribution paradigm that is scalable, ubiquitous, and cost effective. It does not rely on the end-to-end connectivity and can tolerate frequent and long network disruptions. It relies on in-network collaborative data storage and explores node mobility to disseminate data to the destinations. Examples of such mobile nodes are pedestrians and all types of vehicles.

Within a mobile peer-to-peer data dissemination framework, we focus on designing data forwarding and caching algorithms under the constraints of long network disconnections, dynamic network topology, limited contact duration per node meeting, and limited capabilities of mobile devices. Our work assumes the following scenario: data is organized into channels; there is such a large number of data channels that individual mobile node only cache a limited number of channels, some of which are for its own interests, while others of which are for other nodes' interests. We typically studied two approaches: heuristic based algorithms and utility optimal algorithms. On the heuristic based algorithm, we proposed a class of reputation-based forwarding and caching heuristics where the forwarding and caching decisions maximize global system performance from each node's local view of global system. The reputation of the data channels, which is essentially the estimated popularities, is estimated using a modified Bayesian framework, integrating both first hand and second hand observations. To design optimal forwarding and caching schemes, we take a utility optimal approach where each data channel is assigned a utility and analytically treats multiple channel data dissemination as a resource allocation problem where the goal is to maximize the aggregate utility per channel. We first derived a close-form expression of channel dissemination delay as a function of number of relaying nodes using Ordinary Differential Equations (ODEs). Then we proposed a centralized Greedy algorithm and

fully decentralized Metropolis-Hasting algorithm for data forwarding and caching to achieve optimal system utility in the form of aggregate utility per data channel. Finally, we also proposed a Heterogeneous Community-based Random Way Point (HC-RWP) mobility model which captures the properties of real human mobility.

To the best of our knowledge, our work is the first contributions on optimal mobile peer-to-peer data dissemination of multiple data channels over a delay-tolerant opportunistic network. The results presented in this thesis are useful for designing a next generation wireless content distribution system that is ubiquitous, scalable, and cost effective.

1. Introduction

1.1 Motivation

With the emerging User-Generated Content (UGC) service, we are observing a paradigm shift in the way electronic content is created and consumed [45]. Whereas published news, photographs, and audio programs have traditionally been produced by a small group of professionals, technology today allows more and more content to be provided by the mobile users themselves, for a broad community of people with common interests [45]. Examples are podcasts, blogs, Wikipedia, or social platforms such as MySpace, YouTube, or Facebook. Providing ubiquitous UGC sharing while people are on the move is of significant interest for both content publishers and content consumers. The current two approaches of wireless content distribution are via either 3G cellular networks or 802.11 wireless networks. However, while UGC becomes more and more popular, the amount of data created by a larger number of users is overwhelmingly larger than the data created by smaller group of professionals. Even if the 3G cellular network provides good coverage as well as continuous access to content, the capacity limits of a cell can quickly become saturated if content upload and download becomes popular. Furthermore, 802.11 networks do not provide seamless coverage. This motivates us to envision a new wireless content distribution paradigm that can alleviate the above capacity and coverage constraints. Secondly, in UGC, the content is not the "King", but the UGC search engine is [1]. As there are much more content and choices, user may have difficulty in searching and obtain their favourite content in a timely and efficient manner via Internet-based search engines. Localized search engines and localized data storage are desired.

Along another line, in the last few years, there has been a great increase in the number of small devices such as PDAs, laptops, smart phones. Besides their wireless connectivity to cellular networks, those devices are often equipped with a short-range wireless networking capability such as Bluetooth and 802.11. By exploring that local cache and short-range wireless connectivity, we can envision a new content sharing paradigm as an alternative to legacy wireless content distribution. Indeed, there are plenty of real scenarios that short-range wireless connectivity and local cache could be explored. A recent study shows that the amount of time people spending travelling to/from work is significant. For example, average commuters living in big cities in the UK spent 139 hours a year travelling to and from work, with the extreme case of a whole month per year for Londoners [2]. Most commuters prefer public transport (e.g. bus, train, subway) for the reason of cost and increasing length of distance being travelled, e.g. the London tube carries an average of 3.4 million people every weekday. Thus, the large amount of commuters with short range wireless interfaces, the large amount of time commuters spent together in public transportation, and commuters being routinely in contact, offers new possibilities for short range wireless interfaces and local cache based content distribution.

Motivated by the above two trends, several researchers propose a mobile P2P content distribution paradigm over opportunistic networks that decouples sharing from traditional Internet based platforms [36] [45]. It relies on a virtual fleet of mobile users[1] interacting socially and cooperating in order to distribute content in a peer-to-peer fashion over opportunistic contacts between short range wireless devices carried by people or moving vehicles. Transfer opportunities typically arise when people with matching interests meet such places as public transportations, conferences or urban areas in general. The resulting wireless content distribution model reduces the time it takes to obtain new content when on the move. It not only provides totally new opportunities to interact socially and share content with people having similar interests in content, but also offers a much larger network capacity and coverage compared to cellular network as mentioned above.

1.2 Mobile Peer-to-Peer Data Dissemination Architecture

We describe the system architecture of opportunistic mobile peer-to-peer data dissemination in fig (1) (2) (3). Figure (1) shows the content distribution in a hybrid network and hybrid content provider scenario. Firstly, content is disseminated from a content server over the Internet to users that are connected to fixed infrastructure networks or wireless access networks e.g. wireless LAN access points or cellular radio

[1] In the thesis, we use "user" and "node" interchangeably

networks. Secondly, content is also disseminated to users over opportunistic contacts during user mobility and vehicle mobility in a peer-to-peer manner. In terms of content source, on one hand users download traditional Internet content published by professional content providers from servers in the Internet. On the other hand, thanks to Web 2.0, it becomes more and more popular that users publish their personally featured content to all other users by both the infrastructure network and opportunistic direct contact with other users.

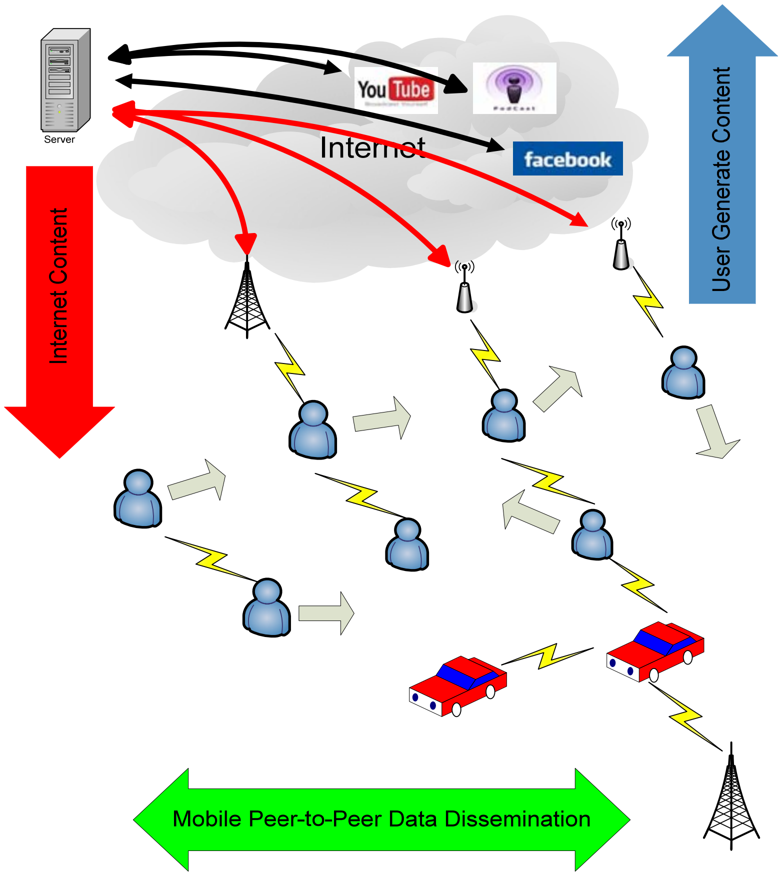

Figure 1: Mobile peer-to-peer content distribution

The protocol stack of mobile peer-to-peer network is shown in figure 2. In contrast to traditional TCP/IP architecture, mobile peer-to-peer system [45] does not require network layer functions, as the routing function is replaced by an opportunistic forwarding and caching function at the application layer. The cache of mobile device is divided into public and private cache which stores public interest content and private interest content respectively. Data forwarding and cache management, as the key function of our system, implements the peer-to-peer data dissemination protocol and manages the all resources of mobile device such as cache, battery, and network bandwidth. Transport layer is in charge of the fragmentation of application data into smaller data chunks such that data chunk can be downloaded in a short contact of node meeting. Forward Error Correction (FEC) function is also provided at transport layer to provide reliable data transfer in a single hop wireless link.

Following [24], in our mobile peer-to-peer dissemination paradigm, the information is disseminated by interest-based pulls from peer nodes during pair-wise node meetings, rather than pushing information to all encounter nodes. During a node meeting, a node may retrieve content for a channel from a peer node, but it is not compulsory. Also, the nodes are only associated in a pair-wise manner, even if there are more neighbours within proximity. The reason is to maximize data exchanged during each node meeting, rather than maximizing network connectivity, given that the contact duration might be short [45].

In figure 3, we show a data structure of cache in the mobile peer-to-peer device. The content is organized into information channels, each of which contains a number of entries. The cache is divided into a public and a private cache which stores channels for its own user's interest and for other users' interests respectively. In this thesis, I do not deeply investigate the incentives for node cooperation. I assume each node is willing to contribute a limited resource of its own for the mutual benefit.

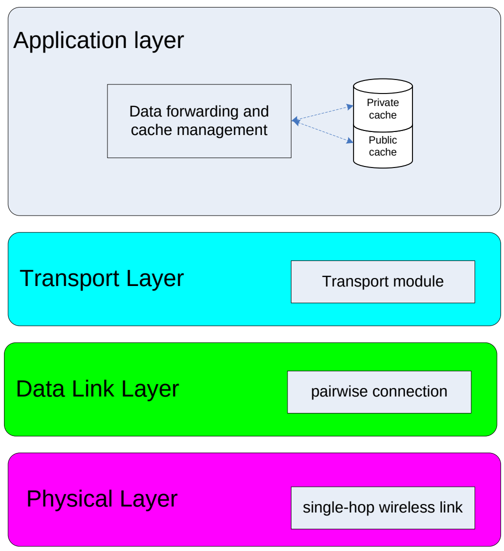

Figure 2: Protocol stack of mobile peer-to-peer network [45]

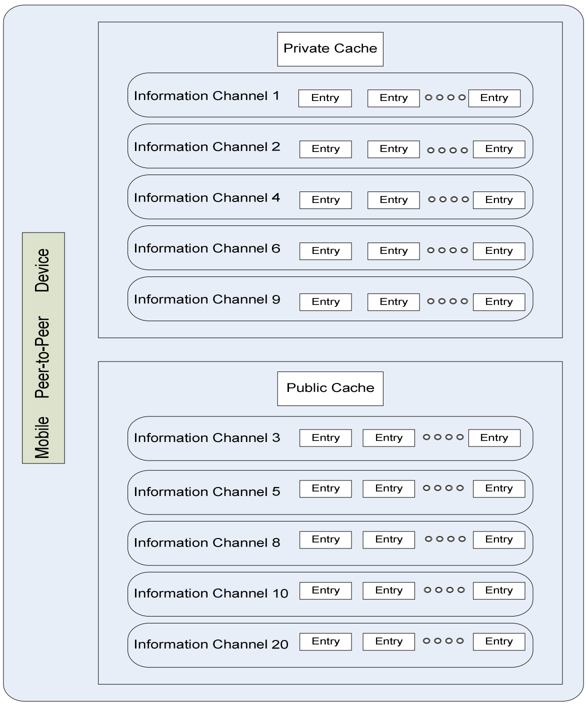

Figure 3: Data structure of cache in the mobile peer-to-peer device [45]

1.3 Benefits of Mobile Peer-to-Peer Data Dissemination

Short-range mobile P2P data sharing has many advantages. In [2], the authors show node mobility can increase the wireless network capacity, provided that the applications are delay-tolerant. Indeed, with a mobile P2P paradigm, mobile node can retrieve content from encountered mobile nodes via short range P2P radio communication and its local cache. This can substantially increase the capacity of wireless content distribution that is purely based on 3G cellular networks or 802.11 WLAN. Secondly, mobile P2P content sharing does not require seamless wireless coverage, thus it can be deployed to extend the coverage of 802.11 wireless local area networks. It can also be a stand-alone alternative to infrastructure-based wireless content distribution. Thirdly, from the user's perspective, mobile P2P content sharing can be much more cost-effective than client-server content distribution via cellular or 802.11 wireless networks, especially with respect to roaming users. In particular, continuous connectivity to the Internet will not be available at a low cost for mobile users roaming a metropolitan area. Fourthly, like other Internet-based P2P data sharing paradigms, mobile P2P enables users to publish content more freely with less restriction from a central authority. The terrestrial wireless broadcast channels are highly regulated: the spectrum allocation is strictly guarded; the concessions of publishing content are severely limited and granted on commercial terms and politically decided criteria. The broadcast content is also regulated and sometime subject to censorship. With a mobile P2P paradigm, we can envision an open wireless broadcast system operating on an unlicensed spectrum that anyone can broadcast personal featured content, analogue to broadcasting in the fixed Internet. Last but not least, with Mobile P2P, we can envision an ad-hoc ***Google-like*** service where one can search content from data replicated at the neighbouring or encounter nodes with much higher hit ratio than Internet based search engine. This is motivated by two environment characteristics: the high spatial locality of information in urban areas (e.g. local and general news, sports, and schedules) and the locality of human social interaction. The content provided by the Internet may not best satisfy the interest of the local users, for example, user may be more interested in a video clip of his friend, Mariah Carey, instead of the MTV of the singer Mariah Carey that is usually what Google search will return to you.

1.4 Review of Opportunistic Wireless Networking

In this section, we survey world-wide research activities on various applications of opportunistic wireless network or mobile peer-to-peer network[2].

In the Haggle project, researchers are studying the properties of Pocket Switched Networks (PSN): a type of opportunistic network that exploits encountered mobile devices carried by people (e.g. smart phones and PDAs that users carry in their pockets) to forward messages. Built on top of Delay Tolerant Networking (DTN) architecture, Haggle has a data-centric architecture where applications do not have to concern themselves with the mechanisms of transporting data to the right place, since that is what has made them infrastructure-dependent. By delegating to Haggle the task of propagating data, applications can automatically take advantage of any connection opportunities that arise, both local neighbourhood opportunities and connectivity with servers on the Internet when available. The project has focused on measuring and

[2] Throughout the thesis, we use opportunistic wireless networks and mobile peer-to-peer networks interchangeably

modelling pair-wise contacts between mobile devices. Different mobility traces have been collected and analyzed, including students and researchers in their university and laboratories as well as participants to some international conferences. They found that, for all the traces they studied, both the inter-contact and contact duration distribution can be approximated by power-laws.

In the PodNet project, wireless ad-hoc podcasting is proposed for podcasts sharing and distributing beyond the infrastructure-based networks, by exploiting the short-range wireless communication and local cache of nodes. In analogy to Haggle, the data dissemination is done through encountered mobile devices carried by people, but the focus is on broadcasting the data to a group of destinations instead of unicast. PodNet offers a means for bringing User-Generated Content (UGC) service and bulk content distribution into the wireless content distribution, which is not widely achieved in Cellular networks and WLAN networks due to the limits of wireless network capacity and cost-effectiveness. Instead of routing the content directly to destinations, the content is replicated at intermediate nodes based on application layer solicitation protocol and implicitly routed to destinations by node mobility and node relaying. The application and transport layer are implemented directly on MAC layer. Thus there is no network layer in PodNet. PodNet also employs a receiver-driven concept, where a node solicits podcast feeds based its own interests and forwarding policy thus no information is pushed into the network.

Opportunistic Ad-Hoc Networking can facilitate file sharing type of applications in the context of Vehicular Ad-Hoc network (VANET), such as office-on-wheels and in-car entertainment. People not only want to download music and move trailers while driving, but also location-aware data such as virtual hotel tour clips. However, the classic client-server based content downloading is not efficient in the VANET scenario, because of the short transmission window from the vehicle to the Access Point (AP), the short-lived connectivity between vehicle and Access Point (AP), and the high mobility of vehicles. Instead, based on opportunistic networking, peer-to-peer cooperative content sharing is desired in the vehicular environment. One example is the CarTolerant project, a BitTolerant-style content dissemination system designed to exploit the wireless broadcasting's nature.

Opportunistic Ad-Hoc network can also provide intermittent Internet connectivity to rural and developing areas where the legacy Internet is not cost-effective to deploy. DakNet Project aims to design a very low-cost asynchronous ICT infrastructure to provide connectivity to rural villages in India. Each village has so-called information kiosks consisting of digital storage and short range wireless interfaces. Kiosks can download/upload information to Mobile Access Points (MAP) which are mounted on buses that travel between villages and towns. The information from the town is ferried by the buses by a store-carry-forward paradigm to the villages where user can download information from kiosks. Similarly, the buses also ferry information from the villages to the town in a store-carry-forward way.

Wild-life monitoring is an interesting application of opportunistic networking. Researcher would like to track wild species to deeply study and understand their behaviors and the interactions between each other. They also look into how the human activities changed their effects on the ecosystem. Opportunistic networks provide a reliable, cost-effective and non-intrusive way to monitor large populations of wild animals roaming in vast areas. Typically, a wild animal is mounted with a radio tag with sensing and storage capability. Various radio tags carried by animals measure the environment data and send that information to a sink node which is usually connected to standard Internet. It is generally difficult for a sink node to collect data from all radio tags efficiently, as animal mobility is unpredictable and the area of mobility is vast. By opportunistic networking, a radio tag shares its data with its encountered radio tags and collaboratively collects the data for the sink node in a store-carry-forward manner. Typical examples of wild life monitoring are Shared Wireless Infostation Model (SWIM) and ZebraNet project.

1.5 Research Challenges

In this section, we present several research challenges in mobile peer-to-peer data dissemination over opportunistic networks. These challenges motivate the work presented in this thesis.

In mobile peer-to-peer networking, network traffic is delivered by node relaying and node mobility. Mobility of people or vehicles is usually dynamic and unpredictable.

Mobility patterns of nodes affect the speed, throughput, and reliability of data dissemination in opportunistic network. Thus, understanding the real mobility is vital for designing and evaluating protocols over mobile peer-to-peer networks. In particular, designing mathematical synthetic mobility model is desired for opportunistic network research. The motivations are as follows: new protocol design often relies on simulations which are based on either real mobility trace or synthetic mobility trace from math model. The current real mobility traces are so limited that simulation based on real mobility traces can not be generalized. Neither is it possible to tune the parameters of real traces to study the sensitivity of new protocols. In contrast, simulations based on synthetic math model can provide much more insight in the analysis of protocol performance. So far the study on math modelling of real mobility is still in the early stage, though there have been some preliminary results based on measurement of real human or vehicles mobility. Those measurement studies reveal different views of the inter-contact time distribution of either real pedestrian mobility or vehicular mobility: it can be approximated by either power-law [7] or power-law with an exponential cut-off [11] or exponential distribution [32]. The current limitations are that the number of participants in the experiment is relatively small and the time granularity of the measurement data is low (in the order of hundreds of seconds). The small number of participants may cause the sampling bias on statistic analysis of empirical data. Besides, those mobility experiments only involve one class of participants e.g. conference participants or students in the campus. It is promising to look into the mobility characteristics of large scale participants consisting of multiple classes of mobile nodes (e.g. students, passengers or conference participants) to have a deeper understanding on how different classes of mobile nodes interact.

The next challenge is: how to design an efficient forwarding and caching strategy for information dissemination in a time-variant intermittent-connected wireless networks? Due to node mobility, the network connectivity is highly dynamic and unpredictable. In mobile peer-to-peer network, often there is no end-to-end path between the source and destination. Classic end-to-end proactive and reactive unicast/multicast routing protocols may not work efficiently, because routing tables need to be updated and exchanged between neighbouring nodes frequently (due to the time-variant network connectivity). These produce a large amount of control traffic which may dramatically slow down the network throughput. Instead, traffic is relayed by encountered nodes in a hop-to-hop basis from source to the destination. At each contact between two nodes, each of the two nodes locally decides which data to relay for both their own interests and other nodes' interests. Apparently, the opportunistic network is a resource-constrained network in the sense that: each node meets other nodes only from time to time and the inter-contact time between the same pair of nodes can be very long; during each node meeting, a pair of nodes only have limited contact time before they move away from radio range thus can only exchange limited amounts of data; nodes may be only willing to share limited power and cache for helping to disseminate information for the public good. Thus, content forwarding and cache management is essentially a distributed resource allocation problem that should optimize network resource usage for best possible Quality of Service (QoS) of end users. There are three research sub-questions: 1) what are suitable performance metrics for evaluating dissemination strategies; 2) what is the local policy of data forwarding and caching during a node meeting to achieve a well-defined global optimal objective such as the aggregate QoS over all users; 3) local policy for optimal content dissemination relies on exploring context information of the network e.g. social network of mobile node, content popularity, and content rarity etc. What is the context information to explore for optimal content dissemination? How can we efficiently share and disseminate context information?

Thirdly, the utility of mobile P2P coexistence with infrastructure-based wireless content distribution needs to be well understood. It is essential to understand the benefit of Mobile P2P before studying its performance and feasibility. It is shown that there is a phase transition where infrastructure could significantly improve the performance of opportunistic networks [5]. Still, further studies on utility of mobile peer-to-peer are desired. For instance, it could be interesting to compare the performance of mobile peer-to-peer system to the cellular system in terms of capacity and coverage. I also believe mobile peer-to-peer data dissemination relies not only on mobile opportunistic contacts but also on a certain amount of infrastructure network to control data dissemination and ensure security and payment functions. Thus, supporting security and payment functions in mobile peer-to-peer system is another research challenge.

1.6 Thesis Contributions

We present several contributions in this thesis:

In the context of mobile peer-to-peer data dissemination over pedestrian opportunistic network, we propose and evaluate a class of heuristics of data forwarding and cache management for collaborative information dissemination. Those heuristics typically decide which node to help forward which channel under the constraints of limited contact time, long inter-contact time, limited cache size, and limited energy of the mobile device. Those heuristics rely on the locally estimated global channel popularity. We propose a Bayesian framework based reputation system that can efficiently estimate information channel popularity in a distributed way by both direct observations and second hand observations shared by encounter nodes. We also propose two performance metrics for evaluating mobile peer-to-peer data dissemination: Recall and Precision, which are used in the area of Information Retrieval (IR).

We analytically study the utility optimal framework for collaborative ad-hoc channel dissemination over general mobile peer-to-peer networks e.g. pedestrian networks or vehicular networks. By Ordinary Differential Equations (ODE), we show the dissemination delay of information channels can be represented as a function of the number of nodes that relay/forward this channel, under a random mixing assumption. We propose a framework for optimizing the dissemination of multiple information channels in wireless ad-hoc networks. The optimization is with respect to dissemination times of individual channels subject to the end-user cache capacity requirement. To be specific, in a centralized setting with global knowledge, we employ the Greedy algorithm to allocate which node forwards which channel for the optimal global utility. Then we propose a practically decentralized Metropolis-Hasting algorithm that can converge fast to the optimal solution by Greedy and does not require any global knowledge of the network. We have done extensive simulations to compare utility optimal data dissemination with other heuristics over both real mobility traces and real information channel subscription traces. The results indicate our optimal data dissemination can substantially outperform the previous heuristics in various scenarios. We also propose a variant of the Metropolis-Hasting algorithm that accounts for battery saving at individual nodes.

We propose a mobility model for simulating opportunistic pedestrian network: Heterogeneous Community based Random Way Point (HC-RWP). It captures the important properties of real human mobility traces, namely *node heterogeneousness, space heterogeneousness, (short term) time heterogeneousness, (long term) time periodicity.*

This thesis is structured as follows:

- Chapter 2 reviews related work of my thesis and highlights the novel aspects of the thesis
- Chapter 3 summarizes the original work in this thesis
- Chapter 4 concludes the thesis and suggest directions of future work
- Four main research papers are listed in the end of the thesis

2. Related Work

In this section, we survey work related to the research topic of my thesis. Firstly, our mobile peer-to-peer data dissemination is delay-tolerant in nature thus falls into the catalogue of Delay-Tolerant Networks (DTNs) research. We present DTNs in section 2.1. In section 2.2, we discuss a type of highly mobile DTNs named opportunistic network, which our mobile peer-to-peer data dissemination is built on. Next, I survey a number of research directions within the area of opportunistic networks: mobility modelling (section 2.3), unicast routing (section 2.4), social network based routing (section 2.5), multicast/broadcast routing (section 2.6), mathematical modelling of opportunistic routing (section 2.7), and various wireless data distribution architecture over opportunistic networks (section 2.8).

2.1 Delay-Tolerant Networks （DTNs）

The existing TCP/IP based Internet provides end-to-end communication using a concatenation of potential heterogeneous link-layer technologies, namely IP over anything. There are a number of key assumptions to make the overall performance of the traditional Internet run smoothly: there is an end-to-end path from the source to the destination nodes; there is a reasonable maximum round trip time between the source-destination pair; the end-to-end packet drop probability is low. Those assumptions are not valid in a class of so-called challenged networks where the traditional end-to-end TCP/IP may perform poorly. The examples of challenged networks are Terrestrial Mobile Networks, Exotic Media Networks, Military Ad-Hoc Networks, and Sensor and Actuation Networks.

The Delay Tolerant Network Research Group [39] proposed architecture for challenged networks to support messaging that may be used for delay tolerant applications. This architecture essentially is a message based store-and-forward overlay network that leverages a set of convergence layers to adapt to a wide variety of underlying transports. In addition, the architecture also supports novel approaches to application structuring and programming interfaces, fragmentation, reliability, and persistent state management. Various routing strategies in DTN have been addressed by Kevin Fall in his paper [40].

Our mobile peer-to-peer data dissemination relies on opportunistic data forwarding during node meetings. There rarely exists end-to-end connectivity between the source and destination. The network disconnections could be long and frequent. In nature, our mobile peer-to-peer network falls into the broader catalogue of Delay Tolerant Network (DTNs).

2.2 Opportunistic Networks

As one type of Delay Tolerant Network, Opportunistic Networks focus on mobile ad-hoc DTNs, where routes are built dynamically between the source and destination, and any possible intermediate node can be used opportunistically to ferry data as required. Opportunistic network is an evolution of mobile ad-hoc networks (MANET), when researchers start bringing MANET research from theory to practice [3]. In contrast to MANET, opportunistic networks do not assume that there exists an end-to-end connectivity between source and destination nodes, which is usually an unrealistic assumption in MANET research. Thus, instead of relying on end-to-end MANET routing protocols such as AODV and DSR, the data is delivered through one hop data transmission in opportunistic node encounters, intermediate node storage, and intermediate node mobility. In the literature, the above is also known as *Store-Carry-Forward* paradigm [4]. Also, opportunistic networks are not completely infrastructure less wireless network (which is the case for MANET). It indeed requires certain infrastructure for the phase transition [5] seen for coverage, the injection of original data, and for the identity and payment mechanism.

Our mobile peer-to-peer data dissemination is built on top of opportunistic networks. It explores short-range wireless connectivity to provide scalable and localized data sharing and dissemination.

2.3 Mobility Modeling

The first research issue of opportunistic networks is to understand node mobility, i.e. how nodes are able to “Carry” the data in the “Store-Carry-Forward” paradigm. Currently two types of node mobility are of high interest: Pedestrian mobility and Vehicular mobility. Research on node mobility is typically conducted by both experimental measurements and mathematical modelling. Experimental measurements of real node mobility have been done for daily student mobility on university campuses [6], participants mobility at conferences [7], taxi mobility in big city e.g. San Francisco [8], Bus mobility [9]. Typically, each mobile node is mounted with a wireless sensor e.g. a Intel i-mote node that keeps track of the node encounters and the time of the encounter over several days or even several months. Inter-contact time and contact time are typical performance metrics for characterizing node mobility in opportunistic networks. Inter-contact time is the time interval between successive contacts of a specific node pair. Contact time is the time interval that two specific nodes stay connected before they move out of the radio range. Inter-contact time corresponds to how often two nodes meet to send each other messages, while contact time corresponds to how much data two specific nodes can exchange during each contact. In previous studies, inter-contact time and contact time distribution are employed to characterize the various real mobility traces or synthetic models. There are several different opinions on the distribution of inter-contact time and contact time of real mobility traces. An early study of real human mobility is presented in [7], where they observed the inter-contact time can be well approximated by a power-law over the range [10 minutes, 1day]. Their observation is confirmed using eight distinct experiment sets. In [10], the author presents that the inter-contact time of 90% contacts of mobile bus nodes approximately follows an exponential distribution. For a wide range of mobility traces, Karagiannis et al [11] show that inter-contact times are only power-law distributed up to 12 hours, and have an exponential cut-off after that. A possible course for this observation is the daily periodicity people have. Han Cai et al. [12] show that simple random mobility models on boundless areas can produce a power-law distribution of inter-contact times. They also show the exponential cut-off effect is in many cases a side-effect of bounded area. We believe even if simple random mobility models on boundless areas can produce a power-law distribution, it does not necessarily show the general properties of real human mobility, as human mobility is in fact most likely within a bounded area. The assumption of boundless area is not realistic. Author [13] proposes a social network based mobility model. This model is based on the idea that nodes prefer to move to areas with higher social attractivity. Social attractivity is defined as the number of friends in a specific square. Friends can change periodically depending on the time of the day. For instance, nodes meet colleagues as friends in the day and meet their family as friend, instead, in the evening. The paper does not show the inter-contact time distribution behaviors for more than roughly one third of a day. Also, the model does not capture the essential properties such as *node and space heterogeneousness*. In [14], a community-based random walk model is presented. Community is defined as a set of frequently visited physical places. In a concentration period, nodes visit their home community more often than other places. In normal period, nodes pick up community uniformly with equal probability. In contrast, our work assumes nodes have a list of frequently visited places and a list of less frequently visited places. Then, we define community as node with similar mobility patterns which are determined by the set of their most visited places. In other words, our community is node centric, rather than the physical place centric. Moreover, in [14], the authors do not show the inter-contact time and contact-time distribution and their comparison to real mobility traces.

In this thesis, we design a synthetic mobility model Heterogeneous Community Based Random Way Point (HC-RWP) that captures four properties of the real human mobility trace. This is the first model of this kind.

2.4 Unicast Routing in Opportunistic Networks

The second research question is how to unicast route data from the source to destination in a dynamic opportunistic network with time-variant topology. It is a "forward" function for a "store-carry-forward" paradigm. A majority of algorithms are based on controlled replication when a node encounters other nodes [15]. Optimization by reducing the number of copies of the same message has been studied, such as Spray and Wait routing [16] where each message can only have a limited number of copies in the network. Many other approaches calculate the probability of delivery to the destination node, where the metrics are derived from the history node contacts, spatial information, and so forth. Lindgren et al. propose a probabilistic routing approach to enable asynchronous communication among intermittently connected groups of hosts. The calculation of delivery probabilities is based on the period of time of collocation of two hosts. A Message ferrying approach for message delivery is proposed in [17]. The authors propose a proactive solution based on the exploitation of highly mobile nodes called ferries. These nodes move according to pre-defined routes, carrying messages between disconnected portions of the network. Other examples are Mobyspace Routing by Leguay [18], context-based routing by Musolesi [19].

In contrast to unicast routing, my thesis concentrates on data dissemination or broadcasting services where the sets of content sources and destinations are decoupled.

2.5 Social Network Based Routing in Opportunistic Networks

Along another line, social network structure of human has been explored for unicast routing in opportunistic networks. The motivation is to search for characteristics of the network which are more stable than mobility. In the case of opportunistic network formed by people, the people's social relationship may vary much more slowly than the network topology. Therefore, forwarding decisions based on the node's social relationship can be more reliable, efficient and scalable than controlled replication based and delivery probability based routing schemes. Indeed, social networks exhibit the small world phenomenon which comes from the observation that individuals are often linked by a short chain of acquaintances. This is confirmed by Hsu and Helmy who performed an analysis on real world traces of different university campus wireless networks [20]. Their analysis found that node encounters are sufficient to build a connected relationship graph, and it is a small world graph. Based on ego network analysis, SimBet Routing [21] attempts to route the packet through the locally determined node's centrality within the network and the node's social similarity to the destination node. Messages are forwarded towards the node with higher centrality to increase the possibility of finding the potential carrier to the final destination. BUBBLE [22] is based on the simple intuition that people belonging to the same community are likely to meet frequently, and are suitable forwarders for the data destined for members of the same community. They proposed a distributed community detection algorithm and showed its applicability across a diverse set of real traces. Then they evaluated the impact of community and centrality on forwarding, and proposed a hybrid algorithm that selects centrality nodes and community members of the destinations as relays. They have shown the performance superiority of BUBBLE in a flat community structure and left the case of hierarchical community structure for a future study.

In contrast to social network based routing, my thesis takes a data centric routing approach, where the context information of the data is explored instead of the context information of mobile nodes.

2.6 Multicast/broadcast Routing in Opportunistic Networks

The third research question is how to multicast/broadcast data in opportunistic networks. While broadcasting has attracted a lot of the researchers' interest, the work presented in [23] concentrates on DTN multicast routing and temporal issues for delay tolerant networking, trying to account for temporal group membership. To be specific, authors define multicast semantic models that allow users to explicitly specify temporal constraints on group membership and message delivery. These semantic models clearly define the intended receivers of messages and have various applications in DTN environments. Then several classes of multicast routing algorithms are proposed based on semantic models. In [24], the authors propose a receiver-centric delay tolerant broadcasting concept over pedestrian opportunistic networks. In contrast to previous work, data is distributed to the potential destinations by an interest-based pull of the relaying nodes. Thus, there is no data flooding in the network, as a node pulls data from the peer node only if it is interested. The receiver group is completely open (in a publish/subscribe style), and there is no need to maintain the group membership of a multicast group. Yoneki in [25] designed a publish/subscribe communication overlay based on the distributed detection of social groups by means of centrality measures [25]. By uncovering the social community structure and centrality of real human mobility traces, a backbone overlay network is built up for publish/subscribe and point-to-multipoint asynchronous communication. While [25] relies on the detection of communities for event notification, [26] any type of socially-aware publish/subscribe system is based on contacts between pairs of hosts. To be specific, the authors propose SocialCast, a routing framework for publish-subscribe that exploits predictions based on metrics of social interaction (e.g., patterns of movements among communities) to identify the best information carriers.

My work falls into this research direction of opportunistic networking. Most of the existing works concentrate on heuristics-based data dissemination schemes which may only achieve sub-optimal system performance. My work is on optimal data dissemination schemes and proposes a practical and distributed algorithm that converges nicely to the optimal data dissemination scheme. Moreover, my work is on dissemination of a large number of information channels, where previous work has either focused on a single information channel or a small number of information channels. We also incorporate the resource constraints of opportunistic network into our framework.

2.7 Mathematical Modeling of Routing in Opportunistic Networks

In opportunistic delay tolerant networking, analytical mode based on either epidemic theory or Markov chains have been used to study the performance of various unicast and multicast broadcast routing approaches. Those models are mostly inspired by the mathematical theory of epidemic modeling [27] [28] which is essentially about the spreading of infectious diseases among individuals. To be specific, epidemic modeling concerns the dynamics of how healthy and susceptible individuals become infected through contact with infected individuals and how immunization affects the spreading process. Recognizing the similarities between epidemic routing and the spread of infectious diseases, the shared wireless Infostation model [29] used Ordinary Differential Equation (ODE) models adapted from infectious disease-spread modeling to study the source-to-destination delivery delay under the basic epidemic routing scheme, and then adopted Markovian models to study other performance metrics. In [30], a Markov model is employed to evaluate the tradeoffs in the two-hop multicopy and unrestricted multicopy opportunistic routing protocols. The author accurately models message delay in opportunistic networks where nodes relay messages and the networks are sparsely populated. They also proved that the assumption of independent and exponentially distributed inter-contact times is a good approximation for common random mobility models, such as random waypoint and random direction models. [31] defined a unified Ordinary Differential Equation (ODE) model to study epidemic routing and its variations. The ODE models appear as fluid limits of Markovian models under the appropriate scaling as the number of nodes grows. In general, there is a trade-off on using Markovian models or ODE models: While Markovian models can more accurately capture the behaviour of a system by providing full distribution of interested performance metrics, it is not scalable with the number of nodes and becomes impractical for a large system. In contrast, ODE is especially suitable for a large system and scales well with an increase of nodes. It only can evaluate the moments of the distributions of performance metrics. [32] applied ODE models to study the delay performance of vehicular opportunistic networks enhanced by relays, base stations, and meshes respectively. They derived dimensioning guidelines of deploying hybrid wireless networks consisting of mobile-to-mobile routing and mobile-to-infrastructure routing. In particular, deploying relays and meshes are much more cost-effect than base stations to achieve a given delay performance. Also, a small amount of infrastructure is much more superior to a large number of mobile nodes capable of mobile-to-mobile routing to achieve a given delay performance. [33] proposed an ODE model for a network coding based epidemic routing protocol. They showed the superiority of a network coding based approach when the bandwidth and node cache is limited. Finally, the age of single epidemics was recently characterized in [34] based on partial differential equations (PDEs) which are then transformed to ODE problems.

My work builds on ODE models for broadcast channel dissemination time of multiple channels, whereas previous ODE models only deal single information channel and unicast data delivery delay.

2.8 Wireless Content Distribution over Opportunistic Networks

A number of approaches have been developed in recent years to exploit the wireless connectivity of mobile portable devices and deliver localized content sharing.

PodNet project [35] extends the internet-based podcasting service into ad-hoc domains. When mobile nodes are not connected to a fixed-infrastructure network or a docking station they operate in disruption tolerant mode. In this mode they utilize node-to-node contact opportunities, which arise as nodes move around, to solicit content in a peer-to-peer manner. Nodes only associate in a pair-wise fashion, even if there are multiple neighboring nodes, in order to maximize the data exchanged in a contact (rather than maximize the connectivity to neighboring nodes). There is neither explicit routing nor epidemic style content flooding. Instead, content is delivered to destinations by one-hop interest-based pull from all intermediate relaying nodes, the so-called “receiver-driven broadcasting”.

7DS [36] is a peer-to-peer data sharing architecture, a set of protocols and an implementation enabling the exchange of data among peers that are not necessarily connected to the Internet. Motivated by the high spatial locality of information and the coexistence of a heterogeneous set of information providers, 7DS aims at increasing the data availablility to users roaming a metropolitan area that experience intermittent Internet connectivity.

CarTorrent [37] is a cooperative peer-to-peer file sharing system in a vehicular ad-hoc network. It is similar in operation to BitTorrent, where files are split into small pieces, then downloaded and shared by clients or vehicles. For a given file, CarTorrent clients disseminate their piece availability information via gossiping (which is essentially a k-hop limited scope broadcasting from the originator). Peers then gather statistics such as local topology and piece availability. Statistics are used to select a piece from a peer which is preferably close in proximity e.g. using a select scheme such as Rarest-Closest First. By using Rarest-Closest First, each node first determines the rarest file piece it needs, and then looks for the closest node that has it.

Bluetorrent [38] is another peer-to-peer file sharing system using Bluetooth. Again, in analogy of BitTorrent, files are split into pieces, downloaded, and shared by moving pedestrians. Their goal is to support content download over multiple sessions, thus avoiding the problem of short-lived contact time during node meetings. APs are responsible for seed and spread selected content, as well as management of injection of the content into the system. The work relies on enough people serving the same version of a file to gain the advantage of swarming.

In contrast, my work concerns data forwarding and cache management for general opportunistic network architecture, i.e. either pedestrian or vehicular opportunistic wireless networks. In analogy to PodNet [35], the information is disseminated by a multi-hop pull model. Nodes only associate pair-wise to maximize the data exchanged in each node meeting.

3. Summary of Original Work

In this section, I make a summary of my PhD research work in the form of five research papers. Rather than the original papers, the revised and extended versions of those five papers are enclosed at the end of the thesis. I have also compiled a complete list of published papers in the end of this section. I have selected those four papers to be included in the thesis, because they form the core of my PhD research, mobile peer-to-peer data distribution. The rest of my publications in the list indicate my contributions to other topics within wireless networking.

3.1 Paper A: Reputation Based Content Dissemination for User Generated Wireless Podcasting

Liang Hu, Lars Dittmann, and Jean-Yves Le Boudec

In Proceedings of IEEE Wireless Communication and Networking Conference (WCNC) 2009, Budapest, Hungary, April 2009

Summary: This paper proposes a reputation based data forwarding and caching heuristics for user-generated wireless podcasting. Firstly, we propose three heuristics of data forwarding and cache management, taking into account the resource constraints of limited cache size, limited contact time, and limited power. We also propose two new performance metrics Recall and Precision to evaluate the performance of various heuristics. Secondly, data forwarding and cache management requires knowledge of context information of global podcast channels e.g. channel popularity or channel scarcity. To locally estimate global channel popularity information at each node, a Bayesian framework based reputation system is proposed. Using the reputation system, each node can locally learn global channel popularity which is essential for data forwarding and cache management decisions.

The distributed reputation system consists of three elements: First hand observations by a modified standard Bayesian framework with an exponential forgetting factor, Second hand observations shared by encounter nodes, and a merger of the first hand observations with second hand observations using a linear opinion pool. To protect against false second hand information spread, a deviation test is used in merging second hand information.

We evaluate the reputation-based data dissemination heuristics through extensive discrete event simulations under a common mobility model, the Random Way-Point (RWP) model. The simulation results show that Most-Most heuristic always performs best among all heuristics, under the impact of varying cache size and number of channels. The Most-Most heuristic means "always forwards and cache the most popular channel first (locally most popular channels available at two meeting nodes)". We also demonstrate that, in terms of estimating channel popularity, Bayesian based reputation system always outperforms the history-based rank scheme, because it utilizes not only first hand observations of channel popularity but also second hand observations shared from encounter nodes. In particular, the reputation system far outperforms history based rank when the public cache size is small or when the Zipf exponent is small (typical less than 1). Finally, we also show that the reputation system is robust against rational lying nodes which pass false channel reputation.

3.2 Paper B: Optimal Channel Choice for Collaborative Ad-Hoc Dissemination

Liang Hu, Jean-Yves Le Boudec and Milan Vojnovic

Submitted to IEEE 29th Annual International Conference on Computer Communication (INFOCOM), San Diego, USA, 2010

Summary: We propose an optimal data dissemination framework for multiple information channel broadcasting services over delay-tolerant opportunistic networks. Previous heuristics based approaches which only have an incidental effect on maximizing performance metrics, as heuristics achieve only locally optimal solution. In contrast, our optimal data dissemination framework relies on the analytical model and can intentionally optimize the performance metrics under resource constraints (ensure global optimal solution). Firstly, using fluid limits of Markov process, we formulate the multiple channel information dissemination as a set of Ordinary Differentiate Equation (ODE) models. We obtain the dissemination delay for each information channel as a function of number of forwarding nodes under the assumption that node meetings are random-mixing. Secondly, we show that maximizing the system social welfare is equivalent to an assignment problem (i.e. which node forwards which channel) whose solution can be obtained in a centralized Greedy algorithm. Thirdly, we show the centralized Greedy algorithm can be approximated by a practically distributed Metropolis-Hasting algorithm such that each node can locally achieve optimal channel assignments with respect to the optimal system welfare without any central control and global knowledge of the network.

By discrete event simulation, we evaluate the performance of Greedy algorithm over real traces of Zune which is a real podcasting user subscriptions data. The simulation results show that the optimal channel assignment by Greedy algorithm substantially outperforms heuristics that were used in the past, under both random-mixing node meeting patterns. Secondly, we compare optimal channel forwarding by Greedy algorithm with other heuristics under real mobility traces. We demonstrate the optimal channel forwarding algorithm achieves significant performance gain over other heuristics. Thirdly, we simulate Metropolis-Hasting based distributed algorithm and show it convergences efficiently to the optimal solution by Greedy algorithm for a wide range of simulation parameters (e.g. large and small user population, large and small number of channels) in the absence of central control and global knowledge of the network. To this end, we show the Metropolis-Hasting algorithm is a practical distributed algorithm that enables individual node to achieve optimal system performance.

3.3 Paper C: Reputation System for User-Generated Podcasting under Community based Mobility Model

Liang Hu, Lars Dittmann

In Proceedings of ICST/ACM Wireless Internet Conference (WICON'08), November 17-19, 2008, Maui, Hawaii, USA.

Summary: In this paper, we propose a Community-based Random Way Point (C-RWP) mobility model and a heterogeneous channel popularity model. C-RWP captures the "clustering" effect of realistic human mobility: The mobility of nodes tends to be localized in certain geographical areas where they frequently meet other nodes with similar social roles e.g. workmate, classmate; conversely, nodes only occasionally meet nodes with dissimilar social roles. The heterogeneous channel popularity model captures diverse interests of information channels for different communities of users, which is also observed in traffic traces of Internet-based user-generated services such as YouTube.

Then we evaluate the performance of the reputation-based mobile peer-to-peer data dissemination framework under the C-RWP model and heterogeneous channel popularity model. In particular, we are interesting in the performance of distributed channel popularities estimation algorithms in the environment where the channel popularity information can not propagate efficiently throughout the network because of localized node mobility and heterogeneous channel popularity. We compare the Bayesian framework based reputation system with history-based rank scheme. By discrete event simulation, we show that Bayesian framework based reputation system is especially useful in the environment of localized node mobility and heterogeneous channel popularity model. Using both first hand observations and second hand observations, it far outperforms other schemes that only use first hand observations such as history-based rank scheme. We also identify the localized mobility alone does not have impact on the superiority of reputation system over history-based rank. Instead, heterogeneous channel popularity combined with localized node mobility does have an impact on the superiority of reputation system over history-based rank.

3.4 Paper D: Heterogeneous Community-based Mobility Model for Human Opportunistic Network

Liang Hu, Lars Dittmann

In Proceedings of IEEE Wireless and Mobile Computing, Networking and Communications Conference (IEEE WiMob) 2009, Morocco

Summary: We proposed a Heterogeneous Community-based Random Way Point (HC-RWP) mobility model for simulation studies of wireless networks, in particular for delay-tolerant opportunistic networks. The HC-RWP captures four properties of real human mobility: *node heterogeneousness, space heterogeneousness and (short term) time heterogeneousness, and (long term) time periodicity.* Those properties are both based on intuitive observations of daily human mobility and analysis of wide range of real human mobility traces reported in literatures.

We evaluate and validate a HC-RWP model by discrete event simulation. The synthetic mobility traces generated by HC-RWP model well captures the four properties of real human mobility mentioned above. We also studied the CCDF distribution of inter-contact time and contact time of synthetic mobility traces generated by the HC-RWP model, both of which are commonly used performance metrics for characterizing real mobility traces or synthetic mobility models. We show the inter-contact time and contact time distribution of HC-RWP capture the statistical features of real mobility traces.

Other publications during PhD study are listed below:

- *TCP Performance Enhancement For UMTS Access Network*

Liang Hu, SERSC Second International Conference on Future Generation Communication and Networking (FGCN 2008), Hainan Island, China

- *Optimizing TCP Performance Over UMTS With Split TCP Proxy*

Liang Hu, Lars Dittmann, Lecture Notes Computer Science (LNCS) CCIS, 2008
Full conference paper publ. in journal, ChinaCom 2008

- *Review of PHY and LINK Layer Research Challenges of Cognitive Radio Networks*

Liang Hu, Villy.B.Iverson, Lars Dittmann, Euro-FGI HET-NETs 2008, Karlskrona, Sweden

- *Evaluation of End-To-End TCP Performance Over WCDMA*

Liang Hu, 4th Euro-NGI Workshop on Wireless and Mobility, Jan 2008, Barcelona, Spain

4. Conclusion and Future Work

In this thesis, we have explored mobile peer-to-peer data dissemination over opportunistic wireless networks, as an alternative paradigm to traditional content distribution over the Internet. Traditional architecture of data dissemination services over the Internet becomes infeasible and inefficient in many challenged network environments where network Infrastructure is not present or limited and users are highly mobile. Examples of such environments are wild life monitoring, rural networks, vehicular networks and military networks. In those network environments, key assumptions of network connectivity such as end-to-end paths and low round trip time are not held anymore. Thus, classic TCP/IP protocol architecture needs to be re-designed. In addition, even in non-challenged network environments like today's Internet, providing ubiquitous and scalable wireless Internet is still challenging. Both Internet capacity and wireless access network capacity may soon become saturated because of the increasing amount of videos and user-generated content being uploaded according to AT&T [41]. The mobile peer-to-peer data dissemination is one solution to the above challenges. It relies on the *Store-Carry-Forward* paradigm where data is *stored* at mobile nodes for both its own interests and other nodes' interests, *carried* through nodes mobility, and *forwarded* to the potential destinations during opportunistic contacts with other nodes. Source nodes and forwarding nodes never push data to their neighbour nodes. Instead, data dissemination is purely based on an interest-based pull operation by encounter nodes in opportunistic contacts. The data dissemination framework provides a scalable, cost-effective, and optimized solution for localized wireless bulk data distribution and user-generated content sharing in urban areas. Rather than completely structure-less, it does need a small amount of network infrastructure for connecting to external networks on the Internet, for injecting some original data from the Internet, or for security and payment functions.

This thesis covers aspects of efficient multiple-channel data forwarding and cache management algorithms in mobile peer-to-peer data dissemination. Data dissemination over opportunistic networks is challenged by long and frequent network disconnections, dynamic node mobility, limited capability of mobile nodes, and lack of global network information. In the thesis, we study two approaches: 1.heuristics based data forwarding and cache management; 2. utility optimal data forwarding and cache management. We also propose a mobility model of real pedestrian mobility.

For heuristic based data forwarding and cache management, we propose a class of reputation-based data dissemination heuristics. Those heuristics explore the context information of user behaviours, in particular data channel popularity, to decide which data channel to forward and cache at each node encounter for the best achievable Quality of Service (QoS) for end-users. We show that, for the case of a large number of channels or limited cache size, the heuristic that forwards and caches the most popular channels performs best among all heuristics. In contrast, for the cases of a small number of channels or large cache size, all heuristics perform nearly the same i.e. uniform strategy that does not require knowing any context information performs as good as the one that forwards most popular channels. We also argue that, for user-generated content, the context information may not propagate to the entire network efficiently, especially when node mobility is localized, node's interest is localized and community based. To alleviate this problem, we propose a distributed reputation system based on modified Bayesian framework. It enables mobile nodes locally learn the context information of data channels by integrating first hand observations and second hand observations shared by its encounter nodes. Compared to the other heuristic that is only based on first hand observation, the reputation system far outperforms history-based rank when the public cache size is small and Zipf exponent is small. In cases of heterogeneous localized channel popularity model and community-based localized node mobility, history-based rank is not able to estimate any channel popularity information, while reputation system is still able to efficiently estimate most popular channels.

Heuristics are of low complexity for implementation, but may be sub-optimal with respects to system performance. To be specific, although each node runs heuristics to decide which channel to forward and cache and which one to drop (among channels locally cached at two meeting nodes), it does not know its effects on global system performance. In other words, there is no clear mapping between heuristics and system performance metrics. Thus, as an important further step, we study a utility optimal channel dissemination framework where we assign a utility to each data channel. The utility function is defined as a concave decreasing function of channel dissemination time, which captures the decreasing happiness of users as dissemination delay increases. Under assumption of random mixing node meetings, we derived a close-form asymptotic expression of the channel dissemination delay as a function of number of forwarding nodes, using mean field theory and Ordinary Differential Equations (ODE). Then we prove that the utility optimization problem is equivalent to a problem of assigning forwarding nodes to given channels and propose centralized Greedy algorithm to optimally allocate forwarding nodes to each channel so as to maximize well defined global system welfare, e.g. minimum aggregate dissemination time over all channels and minimum aggregate dissemination time over all users, subject to the constraint of limited cache size per node. To make utility optimal framework practical and implementable, we propose a distributed Metropolis-Hasting sampling algorithm that can be implemented locally at each node to efficiently approximate a centralized Greedy algorithm, without any central control and centralized knowledge of global network states. Our results show the following observations: 1.under a random-mixing assumption and using Zune data traces of real podcast user subscriptions, the centralized optimal solution by Greedy indeed substantially outperforms centralized versions of heuristics that are used in the previous studies; 2.using real mobility traces from the measurement study at campus of Cambridge University, the optimal allocation by Greedy outperforms all heuristics, especially when the number of channels is large and the cache size per node is small. 3. The distributed Metropolis-Hasting algorithm efficiently converges to the optimal Greedy algorithm for various simulation parameters, both large and small user population and large and small numbers of channels. Last but not least, to get deep insight into how system forwarding capacity is assigned over channels, we also studied a relaxed utility optimal assignment problem whose solution can be obtained by convex optimization [44].

Finally, we propose a Heterogeneous Community-based Random Way-Point (HC-RWP) mobility model for simulation studies of opportunistic networks. It captures four important properties of real human mobility: *node heterogeneousness, space heterogeneousness, (short term) time heterogeneousness, (long term) time periodicity*. We also show that HC-RWP captures important statistical features of some real mobility traces, measured in terms of CCDF distribution of inter-contact time and contact time.

Our work in this thesis is a first step towards mobile peer-to-peer data dissemination over wireless opportunistic networks, alleviating the capacity and coverage constraints of infrastructure-based wired/wireless Internet for bulk data delivery and user-generated data sharing. It also provides new opportunities for social-aware network applications.

There are several ongoing works that we are currently looking into:

- In our utility optimal channel forwarding and caching framework, the close-form formulation of channel dissemination time is obtained under the assumption of random mixing node meetings. It would be interesting to provide a more general channel dissemination time by relaxing this assumption. We are currently working on ODE formulations for the case of non-random mixing node meetings.
- Secondly, we also plan to study forwarding nodes allocation strategies that can achieve Max-Min fair dissemination time for all channels to provide either channel-centric fairness or user-centric fairness, besides the utility (system welfare) optimal objective. Channel-centric fairness is where each channel generated from content sources receives max-min fair allocation of channel dissemination time, while user-centric fairness is that each channel to which a user subscribes receives max-min fair allocation of channel dissemination time.
- Finally, the utility of mobile P2P data dissemination has not been quantified and fully understood with respect to classic centralized content distribution via the Internet and cellular radio access networks, especially in the context of emerging popular user-generated content sharing and the dramatically increasing amount of online video. We are both analytically and empirically studying the capacity of mobile peer-to-peer data dissemination and comparing its utility with infrastructure based wired and wireless content distribution such as the 3G cellular MBMS system [42].

The work presented in this thesis makes important contributions for building mobile peer-to-peer data dissemination systems over opportunistic people networks as a part of the Future Internet (FI) [43]. The emerging popularity of user generated content sharing, bulk data distribution and millions of online mobile devices provides significant opportunities for peer-to-peer data dissemination over mobile users, as a scalable and cost-effective alternative to traditional Internet. Future directions for mobile peer-to-peer data dissemination include security, payment, and charging functions. Also, a socially-aware data dissemination framework is also promising area, where data forwarding and caching is based on exploring the social ties of the encounter nodes under the claims that social networks exhibit the small world phenomenon which comes from the observation that individuals are often linked by a short chain of acquaintances. Rather than explore the context information of nodes (social ties in the social network), our approach is data centric in the sense that the context information of the data is explored e.g. data popularity. The challenge of socially-aware data dissemination is efficient detection of communities in human social networks. Finally, there is still a need to further understand the mobility of large-scale mobile nodes, as mobility is the main resource for data dissemination in opportunistic networking. Typically, current measurements of real node mobility are limited by either node population or data granularity. In the future, large scale mobility measurement experiments are desired. In the meantime, analytical mobility modelling based on real mobility is needed for deeply understanding of mobile peer-to-peer dissemination performance.

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Paper A

Reputation-based content dissemination for user generated wireless podcasting

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Reputation-based content dissemination for user generated wireless podcasting

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Abstract

User-generated podcasting over human-centric opportunistic network can facilitate user-generated content sharing while humans are on the move beyond the coverage of infrastructure networks. We focus on designing efficient forwarding and cache replacement schemes of such service under the constraints of limited capability of handheld device and limited network capacity. Firstly, we propose and compare a class of reputation based dissemination heuristics for content forwarding and caching, taking into account all the constraints above. Our performance evaluation shows that dissemination heuristic Most-Most always performs best under various scenarios. Secondly, because implementing those heuristics are challenged by the lack of global channel popularity information locally at each node, we design a distributed reputation system based on modified Bayesian framework that enable each node locally estimates the channel popularity. Our reputation system replies on both first hand observations and second hand observations from peer nodes. The performance evaluation shows that reputation system can always well estimate most popular, intermediate and low popular channels, thus outperform schemes purely based on first-hand observations which only well estimate a few most popular channels. Our reputation system is also robust against arbitrary percentage of rational liars.

1. Introduction

In recent years, opportunistic network has become an attractive research area for networking small mobile devices carried by human being, vehicles and animals. Besides unicast routing, dissemination based routing such as [1] is another efficient way to provide seamless wireless content distribution beyond infrastructure network. This dissemination based routing particularly support applications in which the set of user interested in receiving a given data is not known in advance, thus the content source and content receiver are decoupled in a way analogous to the publish-subscribe paradigm. In this paper, we focus on designing reputation-based content forwarding and cache replacement schemes for User-generated Wireless Podcasting (UWP) service over pedestrian human networks. We mainly target at obsolete podcasting service where only the most recent update is of interests and old content is always obsolete by the latest one e.g. short news report distribution or software updates of mobile devices. Author in [1] presents preliminary results on PodNet performance by studying several forwarding heuristics, assuming unlimited cache size, power per node, and few podcast channels. In our work, we focus the user-generated content scenario where each user publishes content to other nodes while they are on the move. We proposed a class of reputation based cache and forwarding algorithms. We study the system performance over a large number of channels under constraints of the limited bandwidth, limited cache size per node, and limited energy per node. Besides, in UWP, obtaining popularity information of podcast channels is significant for the content forwarding and cache replacement decisions. Unlike existing Internet-based user generate service such as YouTube [2] where the content popularity information is made centralized, in ad-hoc podcasting, the channel popularity information is fully distributed throughout the network and dynamic due to nodes' mobility. Thus it is much more difficult for each node to obtain and predict popularity information of global channels. With inaccurate channel popularity information, node may forward the content that future encounter nodes are not interested in. Ultimately, this would lead to low hit ratio of content retrieve, low utilization of both the node contact opportunities and cache storage.

The contributions of this work are two-folds:

Firstly, we propose three forwarding and caching replacement schemes and evaluate their performance assuming the ideal knowledge of channel popularity at each node of the network. We aim at comparing various forwarding and cache replacement schemes under various scenarios. We define two new metrics to quantify the user satisfactions of UWP and efficiency of network resource usage, namely Recall and Precision, both of which are borrowed from the area of Information Retrieve (IR).

Secondly, we design a distributed reputation system based on modified Bayesian framework through which each node can efficiently estimate channel popularity. The main idea of our reputation system is as follows: The popularity of channel is represented by the reputation rating. The reputation system consist of three parts: Firstly, the reputation rating of channels at each node is built and updated by the number of requests to each channel from encounter nodes. This is called the first hand information of channel popularity in the sense that it is each node's direct observation. Secondly, reputation rating is also updated by integrating its encounter nodes' direct observations which is called the second hand information of channel popularity. By dong so, node can learn and adjust popularity information of channels from observations made by others even before having to learn by its own experience. By nodes gossiping the channel reputations, the accurate channel popularity information can propagate much faster throughout the network, especially when the popularity distribution is non-uniform and localized （e.g. video clips in German language is popular in Germany while video clips in Chinese is popular in China）. Moreover, to protect against rumor spread from liars, the second hand information is only accepted if a deviation test is passed. Thirdly, to adapt the channel popularity shifts, both the first hand information and the reputation ratings of each channel decays after each contact. The previous observations are gradually forgotten while more weight is put on recently observations.

To the best of our knowledge, our work is the first attempt to employ Bayesian Framework based reputation system for estimating the content popularity in the context of content dissemination over opportunistic networks. Previous, the Bayesian framework based reputation system has been employed in coping with misbehaviours in mobile ad hoc networks [3]. The security and cooperation aspects of (UWP) are not included in this study. For node cooperation, we assume, to join UWP service, for the mutual benefit, node is required to contribute a minimum amount of its cache and energy for helping caching public interested content.

Note that in this study we only consider obsolete podcast service where only one chunk is kept in each podcast channel at any time. For each channel, the old chunk is always replaced by the new chunk. Examples of obsolete services are large scale software updates, News bulletin etc. In the future work, it is interesting to investigate non-obsolete podcast services where each channel has several chunks.

Research on opportunistic networks has mainly focused on unicast routing issues so far [4]. Instead, we focus on data dissemination routing to support applications in which the set of users interested in receiving a given data are not known in advance. There are mainly two classes of data dissemination routing protocols over human-centric opportunistic networks: protocols based on data/content characteristic (e.g. content popularity, content availability) and protocols based on social characteristics/relations of nodes (e.g. community and centrality of the nodes). The concept of receiver-driven broadcast proposed by Karlsson [5] belongs to class 1 data dissemination protocol. Instead of explicitly pushing public interested content to encounter nodes, each node pulls public interested content from peer node based on its own estimated channel popularity and application layer solicitation protocols [1]. Yet, the channel popularity is estimated only by node's first hand observations and it does not consider the aging of the information. Along another line, as one example of class 2, [6] propose a socially-aware routing framework for content dissemination in human based opportunistic network. In their work, the focus is to explore the social properties of nodes and identify the best content carrier for the specific content based on the social ties of nodes. Our work focuses on the exploring the popularity of podcast channel, instead of nodes' social ties, thus belongs to class 1 data dissemination schemes. The rest of the paper is organized as follows: Section II describes the concept of modified Bayesian framework based reputation system. Section III describes data structure and protocol specification of reputation system based wireless podcasting. Section IV contains the performance evaluation of forwarding and public cache replacement schemes as well as Bayesian framework based reputation system. Section V concludes the paper.

2. Data Structure and Protocol Specification

The cache at each node consists of a private cache (for storing node's private or own interested channels) and a public cache (for storing public or other nodes' interested channels). Each node maintains a table of channel reputation ratings which is used for content forwarding and public cache replacement decisions. As an example, the reputation rating table of node A is shown in table 1.

When two nodes meet, there are two phases on exchanging content. They firstly exchange the updates of their subscribed channels. Secondly, if they remain connected, they start exchange updates of their helped channels in public cache based on a pre-defined local channel forwarding and cache replacement scheme. The public content exchange are based on "pull" operation from receivers, i.e. node proactively ask peer node for the data they are willing to carry for public good based on its local policy. This avoids data flooding throughout the network thus improve service scalability. During public content exchange phase, there are two sub-phases: (a) nodes update the channels that they currently help disseminating; (b) nodes replace the channels that they help disseminating with new channels (from peer node) based on public cache replacement policy. In this work, we assume (a) is done before (b) under the assumption that only limited data can be exchanged in a node contact. In other words, during each node contact, node firstly retrieves new chunks for its subscribed and helped channels. Then if there is remaining contact time, it does the channel replacement i.e. replace the least popular channels with more popular channels. We also evaluate the impact when (b) is done before (a) and it turns out the difference is minor, thus we do not show that results here. (In fact, the cache replacement schemes in this paper are the same as "pick from neighbour" heuristics in paper B.)

Table 1: Reputation Rating Table

Reputation Rating Table at node i

Channel Feeds	First Hand Information	ReputationRating	Entries and Metadata	Private or Public
1	$A_{i,1}, B_{i,1}$	$R_{A,1}$	Entry 1 Entry 2 ……..	Private
3	$A_{i,3}, B_{i,3}$	$R_{A,3}$	Entry 1 Entry 2 ……..	Private
5	$A_{i,5}, B_{i,5}$	$R_{A,5}$	Entry 1 Entry 2 ……..	Private
7	$A_{i,7}, B_{i,7}$	$R_{A,7}$	Entry 1 Entry 2 ……..	Private
9	$A_{i,9}, B_{i,9}$	$R_{A,9}$	Entry 1 Entry 2 ……..	Public
……	……..	……..	…………	……
j	$A_{i,j}, B_{i,j}$	$R_{i,j}$	……….	Public
…..	……..	………	………..	……

Channel Feed: information Channel identifier

$A_{i,j}, B_{i,j}$: first hand information of channel j at node i.

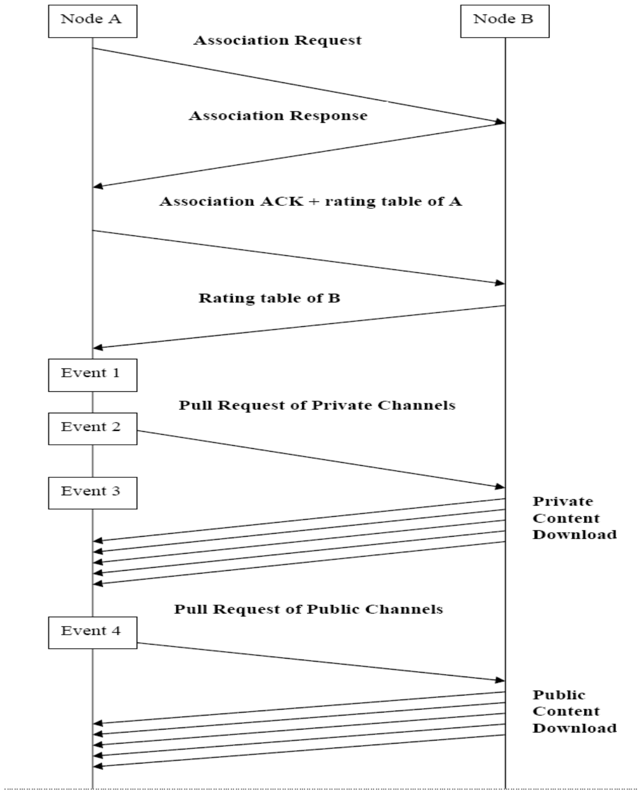
$R_{i,j}$: reputation rating of channel j

Entries and Metadata: A list of entries and their metadata for the information channel

Private or Public: indicator of the information channel that is either subscribed or helped by the node.

In brief, the protocol specification of reputation system based podcasting is as follows: (As two nodes behave in a symmetric way, we only describe behaviours of one node for simplicity reasons. The protocol specification is at application layer, thus the neighbour discovery is not Bluetooth specific.)

1. Idle node periodically broadcast association requests to its neighbours. If it discovers several neighbouring nodes, it randomly selects one node to associate and establish a pair-wise connection.
2. Node updates its estimated popularity of all channels by merging the second hand information from peer based on Bayesian reputation system [Event 1].
3. Node firstly pulls updates of private interested channels from peer node [Event 2].
4. Upon peer node requested updates of its privately interested channels [Event 3], node updates first hand observation of its estimated channel popularity based on Bayesian reputation system (standard Bayesian framework).
5. Node pull content of public interested channels based on its estimated channel popularities and forwarding and cache replacement schemes [Event 4]. Various forwarding and public cache replacement schemes are described below.
6. Content synchronization complete or two nodes move away from the radio coverage.
For detailed description of protocol specification, see the message sequence chart below (suppose node A and node B establish a pair-wise association.).



Public-interested channel forwarding scheme:

Most (M): Based on node's local channel popularity estimation, node firstly forward the content of the most popular public-interested channel from its peer node if there is new update, then the second most popular one, the third most popular one and so on, until the association of two nodes breaks either when they move apart from each other or the data exchange of two nodes complete. The aim of forwarding most popular channel first is to maximize the probability that future encounters would be interested in requesting it.

Probabilistic (P): node decides to forward a public-interested channel with a probability proportional to its popularity (by the node's local estimation). This scheme gives most network capacity to most popularity channels while still gives certain network capacity to intermediate and low popular ones.

Uniform (U): A node decides which channels to forward content with equal probability. The network capacity is evenly given to all the channels exclude the channels that one subscribes. Thus, node does not need to estimate the popularity information of channels for forwarding decisions.

Public cache replacement scheme (public-interested channel replacement scheme): When the public cache of a node is full and there are new public-interested channels at peer node, one has to decide whether to replace channels already in the public cache with new public-interested ones from peer. If it decides so, it also needs to decide which public-interested channels to replace. Suppose node u meets node v where F(u) is list of forwarded channels at node u and F(v) for node v. S(u) and S(v) are the set of subscribed channels for node u and v. During channel replacement, typically node u selects its list of helped channels from the set F(u) U F(v) \ S(u). And node v selects its list of helped channels from the set F(v) U F(u) \ S(v).

Most (M): Only if the new channel from peer is more popular than the least popular public-interested channel in the public cache, node can replace with this new channel. If so, the least popular channel in public cache will be replaced by this new public-interested channel from peer. The channel popularity is based on the node local popularity estimation. In other words, node select the list of helped channels from F(u) U F(v) \ S(u) according to the decreasing channel popularity.

Probabilistic (P): When public cache is full, node select the list of helped channels from F(u) U F(v) \ S(u) with a probability which is proportional to its popularity (based on node local rating table).

Uniform (U): When public cache is full, node select the list of helped channels from F(u) U F(v) \ S(u) with equal probability. Nodes do not need to have the channel popularity information.

3. Bayesian Framework Based Reputation System

3.1 Standard Bayesian Framework

Node i models the popularity of channel j as an actor in the base system as follows. Node i thinks that there is a parameter θ such that the channel i is interested by any node with probability θ. The outcome is drawn independently from observation to observation (node i thinks there is a different θ for different channel j while different node i may have different belief in the parameter θ). The parameters θ are unknown, and node i models this uncertainty by assuming θ itself is drawn according to a distribution (the "prior") that is updated as new observations become available. We use Beta (A, B) as the prior distribution since it is suitable for Bernoulli distribution and the conjugate is also a Beta distribution. (At each node contact, the event that "the channel is requested or not by peer" is a Bernoulli event; The Bernoulli distribution and Beta distribution are conjugate pair i.e. if Beta distribution is prior distribution and Bernoulli distribution is likehood distribution, then the posterior is also Beta distribution). The standard Bayesian procedure is as follows. Initially, the prior is Beta (1, 1), the uniform distribution [0, 1]; this represents absence of information about which θ will be drawn. Then after (f+s) observations during contacts with encounter nodes, say with s times the channel i is requested by encounter nodes while f times it is no requested by encounter nodes. The prior is updated:

$$A := A + s,\ B := B + f\ .$$

If θ, the true unknown value is constant, then after a large number n of contacts:

$$A \approx n\theta,\ B \approx n(1-\theta)$$

And Beta(A, B) becomes closes to a Dirac at θ, as expected. We denote E (Beta (A, B)) as the expectation of Beta (A, B). Thus we can estimate θ as follows:

$$\theta \approx E(Beta(A, B)) = \frac{A}{A+B}$$

3.2 First hand information by modified Bayesian approach

The first hand information for the popularity of channel j at node i is defined as:

$$F_{i,j} = (A_{i,j}, B_{i,j})$$

This represents the parameters of the Beta distribution assumed by node i in its Bayesian view of the popularity of channel j as an actor in the base system. Initially, it is set to (1, 1). The standard Bayesian method gives the same weight to each observation regardless of its time of occurrence. However, the popularity of a podcast channel may change when nodes move between different communities with different channel popularity distribution. For this reason, we add a reputation fading mechanism to give less weight to the past observations, because the latest observations would be more important for estimating current and future popularity of the channel. Assume node i makes one individual observation of channel j during a contact with encounter node. Let s=1 if channel j is requested by the encounter node, and s=0 otherwise. The update is as follows:

$$A_{i,j} := u \bullet A_{i,j} + s\,, \qquad B_{i,j} := u \bullet B_{i,j} + (1-s)$$

The weight u is a discount factor for the past experiences, which serves as the fading mechanism. 0<u<1.

3.3 Reputation Rating and Model Merge

The reputation rating of channel j at node i is defined as $R_{i,j}$:

Initially $R_{i,j} = E(Beta(A_{i,j}, B_{i,j})) = \dfrac{A_{i,j}}{A_{i,j} + A_{i,j}}$, $(A_{i,j}, B_{i,j})$ is set to (1, 1).

It is built and updated on two types of events: (1) when first-hand information is updated by own observations; (2) the second hand information from encounter nodes are accepted and copied. There are two variant of using second hand information from encounter nodes: direct observations (first hand information) from encounter nodes and reputation rating from encounter nodes (the latter one is not considered in this study). For event type (1), the update of reputation rating is the same for the first-hand information updating. Let $s \in \{0, 1\}$ is the observations:

$$A_{i,j} := u \bullet A_{i,j} + s, \qquad B_{i,j} := u \bullet B_{i,j} + (1-s)$$

$$R_{i,j} = E(Beta(A_{i,j}, B_{i,j})) = \frac{A_{i,j}}{A_{i,j} + B_{i,j}}$$

For the case (2), if we assume passing direct observations, the linear pool model is used to merge own reputation rating with direct observations passed from encounter nodes on the condition if the deviation test is passed. Deviation test is used to protect system against false rating from encounter nodes. The idea behind it is that humans only believe the opinions from others only if, to them, it seems likely i.e. it dose not differ too much from their own opinions. Moreover, even if they accepted opinions from others, they only attach less weight to other's opinions than their own opinions. Let the first hand information of channel j at encounter node x:

$$F_{x,j} = (A_{x,j}, B_{x,j})$$

The deviation test is as follows:

$$\text{If } \left| E(Beta(A_{i,j}, B_{i,j}) - E(Beta(A_{x,j}, B_{x,j})) \right| < \text{THS}$$

(THS is a positive constant between 0 and 1(deviation threshold)), then the deviation test is passed and we believe the report from node x is trustworthy. Then, α_i^j , β_i^j are updated by first hand observations of node x using the linear opinion pool model:

$$R_{i,j} = (1-w) \bullet R_{i,j} + w \bullet \frac{A_{x,j}}{A_{x,j} + B_{x,j}} \quad 0<w<1.$$

4. Performance Evaluation

In this section, we firstly compare three forwarding and cache replacement heuristics under the ideal knowledge of channel popularity information at each node. Then, assuming the dissemination heuristic is Most-Most, we study the Bayesian framework based reputation system on estimating channel popularities. We evaluate its performance by a benchmark scheme: history-based rank [1].

A. *Simulation Settings*

The performance evaluation is done with our own discrete event simulator written in C language. It is based on a simple communication model: two modes can communicate with a nominal bit-rate if their geometric distance is smaller than a threshold value (that models the radio range of mobile device). The simulation model does not incorporate link layer issue such as collision or interference, since we simulate a sparsely connected network where the collisions or interference among different associations are rare. We also believe that even when the collision is modelled, the same results can be obtained for the comparisons of various forwarding caching heuristics. For the simulation, we further assume that the setup time for nodes' pair-wise associations is 10 second which includes neighbour discovery time and node synchronization time [7].

We assume a scenario where human beings carry mobile portable device equipped with 802.11b wireless interface. For that purpose, we set nodes move according to Random Way Point (RWP) mobility model with a constant moving speed 1m/s (average human walking speed) and constant pause time 1s. The radio range of each device is assumed to be 38 meters (indoor wireless range of 802.11b) and the nominal rate of the radio device is 2.25 M/s (application layer throughput for single direction is obtained by equally dividing 4.5/2=2.25 M/s per direction). We further assume in total 100 nodes initially uniformly distributed in a square with diameter (1500 m, 1500 m). Nodes only associate pair-wise, even if more than two are within reach of one another. The reason is that the contact duration may be short and it is better to get high throughput by only sharing the transmission capacity between two parties than to get high connectivity. When the contact duration is very long, one might consider the point to multipoint or multi-hop connectivity. Each node can publish one channel to other nodes of the network, but it is not mandatory. For simplicity, we also assume each node generate new contents of its channel periodically in time interval e.g. every 300 second. Besides publishing content, each node is interested in two channels published by other nodes. The global popularity distribution of podcast channels follows Zipf-like distribution. We assume the lower the channel index, the higher the popularity, i.e. channel 0>channel 1>channel 2>channel 3>…channel 99. Thus, the popularity of channel i is given as follows:

$$P_i \sim \frac{1}{(i+1)^a}, \text{ i = 0, 1, 2….99}$$

Each node has 2G bytes cache which consists of public cache and private cache. Each data chunk is 2 M byte, thus downloading one chunk takes 8s with pair-wise association under 802.11b MAC. One chunk is assumed to be a complete and atomic unit and can be self-contained played offline. Each data chunk is assumed to be of the same size. For example, it could be 10 minutes audio of BBC news as a part of 60 minutes BBC news program. The semantic of podcasting service is assumed to be obsolete, where only the most recent chunk of each channel is kept in the cache. For a given channel, once new chunk of that channel is received, the old chunk would be immediately deleted. However, each node can optionally keep its own subscribed chunks in private cache. The total simulated time is 12 hours. The simulation parameters of Bayesian reputation system are THS=0.4, u=0.99. w=0.2.

B. Performance Metrics

To quantify the user satisfaction of ad-hoc podcasting and efficiency of resource usage, the Recall, Precision, and Delay are employed as the performance metrics. Recall is defined as the fraction of node's own subscribed chunks that are successfully received before a deadline T. Precision is defined as the number of subscribed chunks delivered before a deadline T divided by the total number of times that chunks exchanged between peers during the whole simulation process (i.e. one chunk might be forwarded several times). Precision indicates the efficiency of the network resource usage, since the total number of chunks exchanged globally accounts for the total bandwidth and energy consumption throughout the network for successfully delivery of a given number of chunks. Both Recall and Precision are borrowed from the area of Information Retrieve (IR). Delay is defined as the latency between the time when chunk is published and the time when it is received. We believe, for podcast service, the three metrics are equally important.

Recall of node i by time t is defined as:

$$R^i(t) = \frac{X_R^i(t)}{X_p^i(t)}, i = 0,1,2 \ldots. N-1$$

Precision of node i by time t is defined as:

$$P^i(t) = \frac{X_R^i(t)}{X_C^i(t)}, i = 0,1,2 \ldots. N-1$$

N: the total number of nodes. i: the node ID.

$X^i_R(t)$: the number of private subscribed chunks that have been received before a deadline T by node i at time t.

$X^i_P(t)$: the number of private subscribed chunks that have been published from node i's interested channels at time t.

$X^i_C(t)$: the number of times that chunks exchanged during node meetings during the whole simulation process, including both private interested and public subscribed chunks.

Average recall is defined as the average recall over the total number of nodes N. So does the average precision. In this work, we are only interested in the average recall at the end of the simulation and t is set to the max simulated time. The deadline T in our study is also set to the max simulated time.

Delay is defined as $\Delta t = T_{publish} - T_{receive}$. $T_{publish}$ is the time when chunk is published while $T_{receive}$ is the time when it is received. Assume M is the total number of chunks received by all nodes at the end of simulation. The average delay is defined as:

$$\frac{\sum_i \Delta t}{M}, i = 1,2,3 ...... M$$

Note that "Precision" is defined when starting writing the PhD thesis. Thus some of the results show below does not consider "Precision" while other results do consider it.

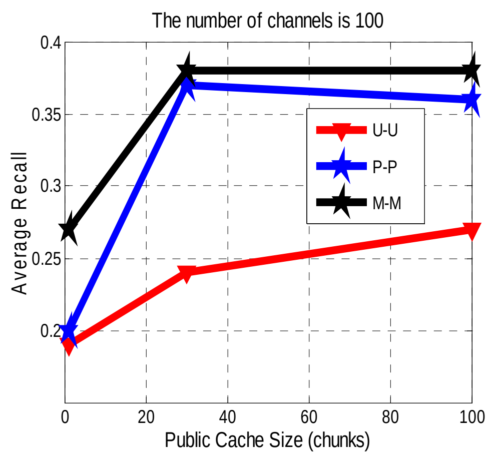
C. Simulation Results

1. Comparison of forwarding and cache replacement schemes under the ideal knowledge of channel popularity

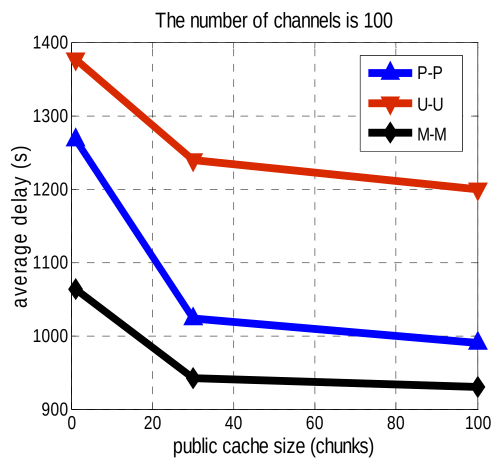
We assume all nodes have prior knowledge of the global channels popularity information and their subscribed channels. We compare the performance of three heuristics of public data forwarding and public cache replacement schemes.

Table 3: Simulation Parameters

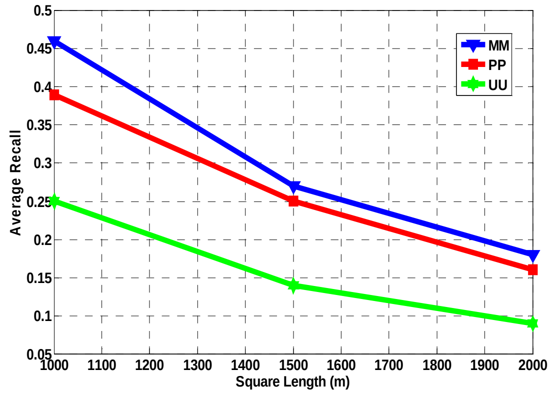
Zipf-like distribution	Publish interval	Public cache size	Number of channels
a=1.0	300 s	1 chunks 30 chunks 100 chunks	100



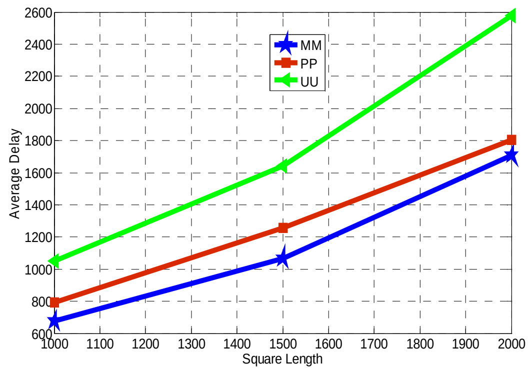
1 (a)



1 (b)



1 (c)



1 (d)

Figure 1: Comparison of forwarding and cache replacement heuristics under the ideal knowledge of channel popularity

Note that we only show the three combinations of forwarding and cache replacement schemes, for the ease of presentation. Though, we have done the full evaluations of all nine possible combinations, from which we found out three combinations are representative. Here, we have the following definitions:

MM: Forwarding scheme is "Most", Cache Replacement is "Most"

PP: Forwarding scheme is "Probabilistic", Cache Replacement is "Probabilistic".

UU: Forwarding scheme is "Uniform", Cache Replacement is "Uniform".

The definitions of "Most", "Uniform" and "Probabilistic" are in section 2.

In figure 1(a) (b), we compare the three heuristics under the impact of public cache size per node. The fixed parameters are defined in table 3. Here we assume node contribute sufficient power for collaborative data dissemination. It is nature to assume that each node is only willing to share a limited public cache for cooperative content sharing, even if they may have large enough cache. By varying the public cache size, node actually vary the degree of their cooperative behaviours. In this case, the public cache size is assumed to be 1, 30 and 100 chunks respectively. The plots show MM always performs best while UU always performs worst in terms of both average recall and average delay. The observation is nature in the sense that: with MM, node always prioritizes forwarding and caching the most popular channels which are very likely to be requested by future encounters, thus network resources are efficiently utilized; In contrast, with UU, node may forward and cache many low popular channels which are little requested, thus the network resources are low utilized. The second observation is: with MM and UU, the recall increases dramatically while the delay decrease dramatically, when public cache varies from 1 chunk to 30 chunks; then, the recall and delay almost keep constant when varying public cache from 30 to 100 chunks. The reason is as follow: the performance is limited by public cache size when the public cache is 1 chunk. Increasing public cache from 1 to 30 chunks gives significant gain. As the cache size becomes 30 or 100 chunks, network performance is determined by pair-wise contact durations. Increasing public cache size from 30 to 100 does not give significant performance improvement, as the network bandwidth is limited by node mobility. We also studied average precision. It turns out that MM achieves always higher average precision than UU under the impact of cache size.

In figure 1(c) (d), we compare the three heuristics under different node densities by varying the RWP square diameters. The public cache size is 30 chunks and other simulations parameters are defined in table 3. We observe MM can achieve almost 50% average recall and 10 minutes average delay when the square length is 1000 meter. The performance decreases as node density becomes sparse at square length 2000 meter, because the node meetings become more infrequent when the node density is low. This calls for deploying infrastructure network to improve network performance. Infrastructure-enhanced ad-hoc podcasting is left for a future study.

Table 4: Simulation Parameters

Zipf-like Distribution	Publish Interval	Public Cache Size	Number of Channels
a=1.0	300 s	30 chunks	20， 50， 100

Next, we study the different heuristics under the various numbers of channels. As shown in fig 2(a) and 2(b), when the number of channel is small (e.g.10, 20), all schemes achieve identical performance of both average recall and average delay. As the number of channels increases, MM and PP performs much better than UU. In particular, when the number of channel is 100, MM can outperform UU almost 100% of average recall and 600 second of average delay. The reason is as follows: for a given channel popularity distribution and fixed number of nodes, when the number of channels is small, all channels are very popular among the nodes. It does not matter how network capacity and public cache capacity are allocated to different channels (according to one specific forwarding and cache replacement scheme). Forwarding and caching any channel would bring a high hit rate for the future encounter nodes. Thus, MM, UU, and PP perform similar in this case. However, as the number of channel increases, the number of unpopular channels increases. In this case, the allocation of network capacity and public cache capacity does matter. With UU scheme, too much network and public cache capacity would be wasted for forwarding and caching unpopular channels which are rarely requested; In contrast, popular channels being highly requested cannot get sufficient network resources. MM can more efficient utilize network resources than UU by allocating most network resources to popular channels which are highly requested and least capacity to unpopular channels which are rarely requested. Thus, MM and PP significantly outperforms UU when the number of channel is large.[3]

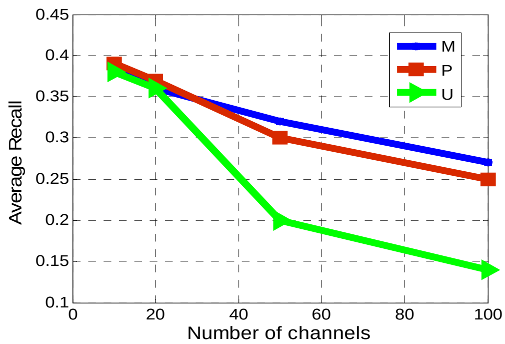


Figure 2 (a)
Average recall under various numbers of channels

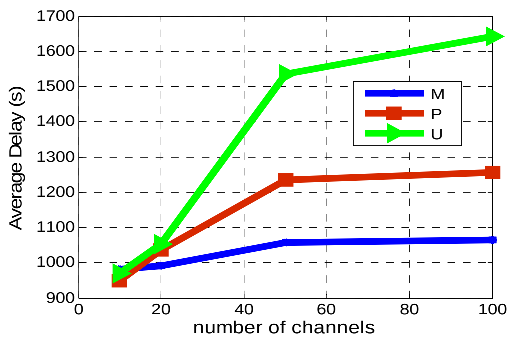
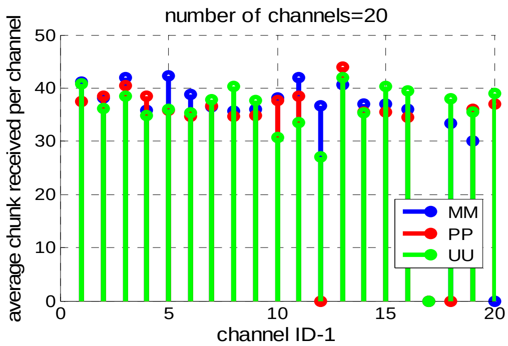


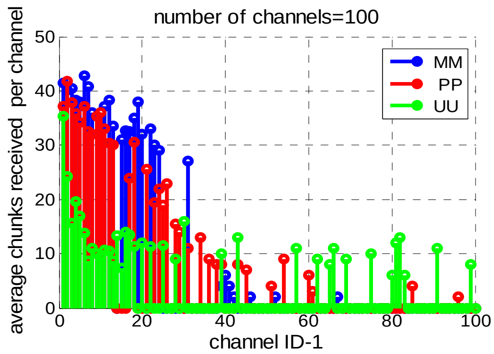
Figure 2 (b)
Average delay under various numbers of channels

Figure 2: Comparison of forwarding and caching heuristics under the number of podcast channels

[3] Paper A and Paper B have different performance metrics, thus one cannot compare the results of paper A and B Thus paper A and B may obain diferent reuslts. Besides, the model in paper B is not perfect, as it does not consider the channel injection rate and multiple entries per channel in the ODE model. Paper B is channel dissemination time centric.



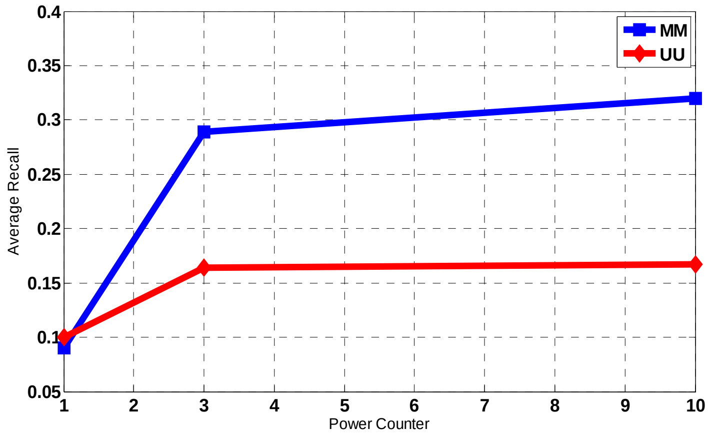
(a)



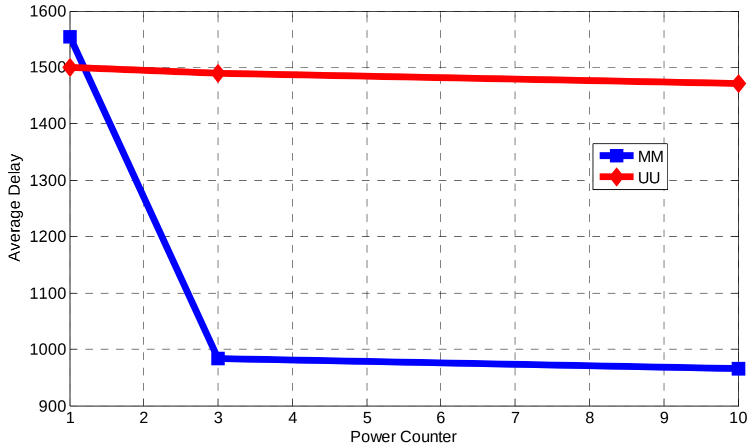
(b)

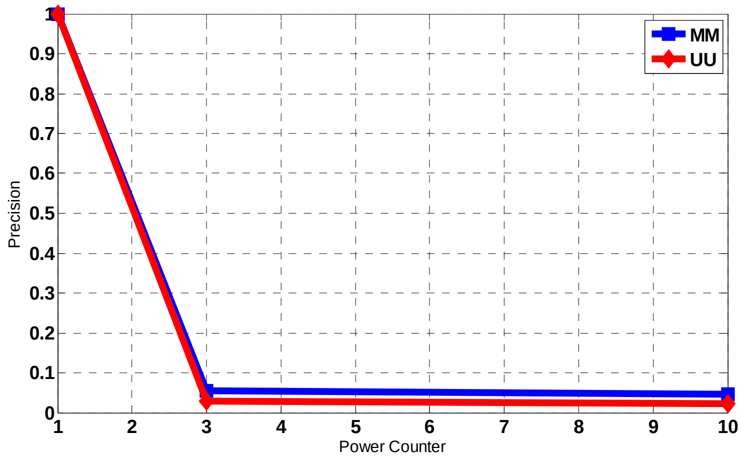
Figure 3: Comparison of forwarding and caching heuristics in terms of channel fairness

Fig 3 (a) (b) shows the average chunks received for each channel, which essentially shows the fairness of ad-hoc podcasting over various channels. When the number of channel is 20, under all schemes, most channels achieve similar average chunks delivery ratio per channel, for which the channel fairness is good; When the number of channel is 100, high popular channels achieve much higher average chunk delivery than low popular channels, especially with MM and PP schemes. In figure 3 (a), channel 16 get zero chunk delivered, because there are no subscribers for channel 16 (given the static assignment of channels to subscribers according to Zipf). This can be changed by generating Zipf distribution (channel subscription) several times and take mean value of average chunk received per channel.



4 (a) (above) and 4 (b) (below)

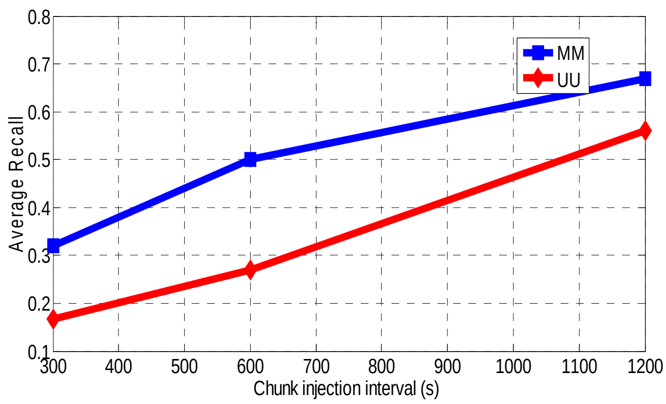




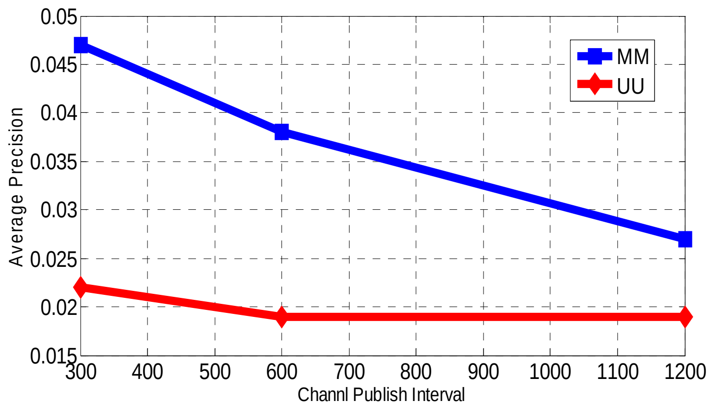
4 (c)

Figure 4: Comparison of forwarding and caching heuristics in terms of energy conservation

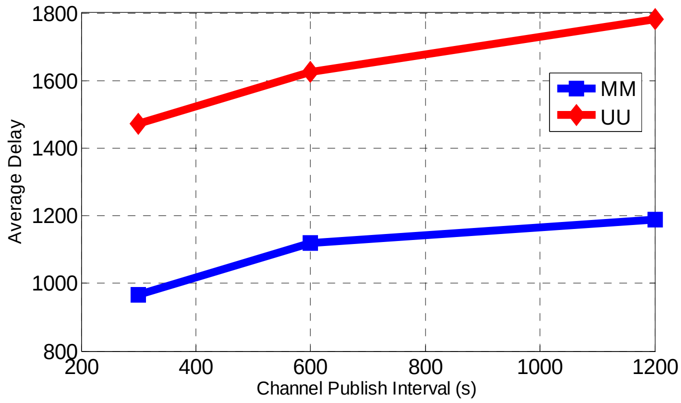
Energy conservation: nodes consume considerable amount of energy for helping forwarding public interested channels. To stimulate node cooperation in the network, it is important to minimize energy consumption at each node while still obtain the best possible global performance. In this work, a simple energy conservation rule is proposed: Assume node takes W unit energy to transmit a chunk to its peer upon peer's request. At each meeting, one node can request peer x number of chunks of public interested channels, where x is limited between [0, Max_Power_Counter]. Thus the max power consumption of helping public interested channel is (Max_Power_Counter*W) unit. We assume the number of channel is 100 and public cache size is 30 chunks. Other parameters are set as in table 3 or 4. In the plots 4 (a) (b) (c), we study the MM and UU by varying Max_Power_Counter. In terms of recall and delay, it shows that an intermediate value of Max_Power_Counter can already gives the same performance as a large value of Power Counter. The reason is that when the Power Counter is large, the network performance is limited by either forwarding or cache schemes. Thus, allowing node consuming more energy for cooperation does not bring performance enhancement. In contrast, the network performance does improve significantly when the Power Counter increases from very small (e.g. 1) to intermediate value (e.g. 3). Even if when the power counter is 0, the average recall is not zero (no public interested channels are disseminated), because the data is still disseminated by subscribed channels at each node.



5 (a)



5 (b)



5 (c)

Figure 5: Comparison of forwarding and caching heuristics in terms of channel injection rate

Injection rate: In fig 5 (a) (b) (c), we vary the channel injection rate by adjusting the channel publish interval. It shows that the average recall increases as the publish interval increases (or channel injection rate decreases). This is caused by the fact that: as the publish interval increases, the probability that one channel (either subscribed or helped by a node) receives a chunk update (from either source node or helping node) increases. As the channel publish interval increases, node have more time to receive the current updates either from source or relays before the current update is obsolete by next update. Secondly, as the publish interval increases, both the number of successful received chunks and number of overhead chunks increase. Due to the fact that the helped channels are much large than the subscribed channel, the average precision decreases as publish interval increases. In fig 5(c), we also observe the average precision of Most-Most heuristic decreases as the publish interval increases, while the average precision of Uniform-Uniforms keeps constant as publish interval increases.

2. Performance evaluation of modified Bayesian framework based reputation system

In realistic case, however channel popularity information is not ideally known at each node. In this section, assuming Most-Most scheme is employed, we evaluate the performance of reputation system by comparing it with history-based rank scheme [1]. With history-based rank, channel popularity is estimated only by node's direct observation that is represented by number of requests per channel from encounter nodes. Typically, node keeps track of the channels that were requested by past encounter nodes and maintains a history-based ranking. Only the requests for the channels of encounter nodes' own interests are counted. The initial condition of history-based rank is set to "1" for all the channels.

We firstly compare the channel popularity evolution over time at node 5 (node ID) for the two channel popularity estimation methods [4]. The channel popularity is represented by the number of requests from encounter nodes and by reputation ratings respectively. We assume the forwarding and data caching heuristic is Most-Most. The fixed simulation parameters are in the table 5:

Table 5: Simulation Parameters

Zipf-like Distribution	Number of Channel	Public Cache Size	Publish Interval
1.5	100	30 chunks	300 s

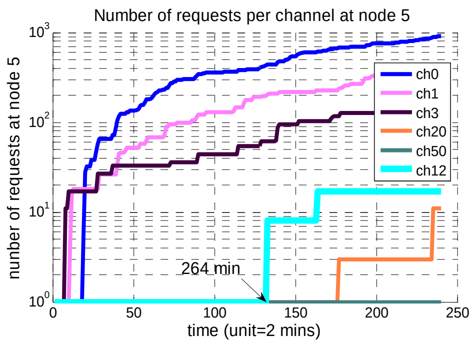


Figure 6
History-based rank: number of requests per channel

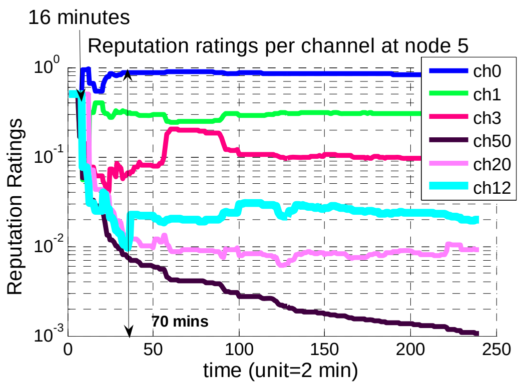


Figure 7
Reputation system: reputation ratings evolution

Fig 6 shows the performance of history-based rank scheme in channel popularity estimation at node 5. Without loss of generality, we take node 5 as an example of evaluating channel popularity estimation. The popularity information for a subset of all the channel are shown, in particular channel 0, 1, 3, 12, 20, and 50, to represent both high and low popular channels. The vertical axis is the number of requests per channel from node 5's encounter nodes, while the horizontal axis is time (unit is two minutes). We observe that the high popular channels (e.g. channel 0, 1, and 3) can be accurately

[4] Node 5 is selected at random among all the nodes.

estimated from the start to the end of the simulation. However, the intermediate and low popular channels (e.g. channel 12, 20, and 50) are not well accurate until a long simulated time has past. There are no observations of popularity information of that channel for a very long simulated time. Take channel 12 for example: only after 264 minutes, node 5 starts to get the popularity information of channel 12. The reason is that, only by node 5's direct observation, it takes a very long time to collect the popularity information of intermediate and low popular channels since there are no requests of those channels at node 5 for a long simulated time. In other words, due to the lack of the direct observations in the past 264 minutes, node 5 would consider channel 12, 20, 50 and 80 as the same popular channels. This can negatively influence the forwarding and cache management decision.

Figure 7 shows reputation system can accurately estimate the popularity of both high popular channels and low popular ones already from the start of the simulation. The vertical axis is the reputation rating per channel from node 5's encounter nodes while the horizontal axis is time (the unit is two minutes). Though the reputation ratings slightly fluctuate in the initial phase of simulation, they get stable very fast. Even if there are not enough direct observations for estimating low popular channels, node can still make use of second hand information from encounter nodes to have a more accurate and faster estimation than history-based rank method. Reputation system outperforms history-based rank also because history-rank may favour channels that constantly meet thus overestimate their popularities. In contrast, reputation system scale the popularity by the total number of observations with the channels, thus it does not give bias to less frequent observed channels.

Next we compare the performance of reputation system with history-based rank under the impact of public cache size and "a" parameter of Zipf-like distribution. We also use the Most-Most scheme under ideal knowledge of channel popularity as the baseline of optimal performance. In figure 8, we assume zipf-a=1. In terms of average recall, reputation system always performs better than history-based rank scheme under various public cache sizes, as shown in figure 8. Especially when the public cache size is small, reputation system can overwhelmingly outperforms history-based rank. In this case, reputation system can outperform 100% over history-based rank when the public cache is 5 chunks. As the public cache decreases, the performance of history-based ranked drops dramatically. The reason of this trend is that history-based rank performs worse as public cache size decreases. Smaller public cache size indicates fewer chunks are likely to be requested per time unit by the encounter nodes. A smaller number of chunks requested by encounter nodes would result in smaller amount of first hand information per time unit, which ultimately brings lower performance of history-based rank. In contrast, Bayesian based reputation system always use first hand and second hand observations. Its performance only drops slightly when the public cache size decreases.

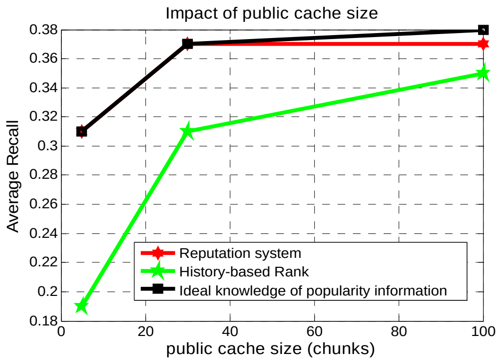


Figure 8:
Average recall under various public cache sizes

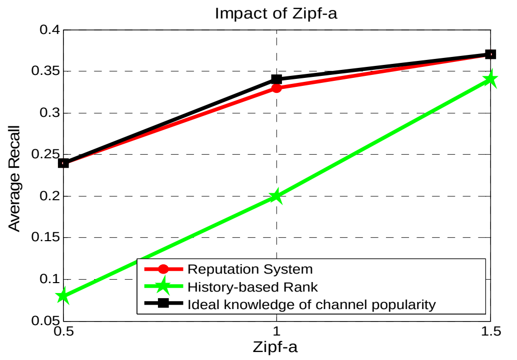


Figure 9:
Average recall under various “a” parameters

Fig 9 shows, as the Zipf-decreases, the performance of history-based rank scheme drops more dramatically than reputation systems in terms of average recall. The reason is that history-based method performs worse than reputation system as the “a” parameter of Zipf-like distribution becomes smaller. The analysis is as follows: for a given “a” Zipf-like distribution, accurate estimations of both most popular and intermediate popular channels are important for the network performance, while low popular ones are not so important because they are rarely requested. History-based rank can only estimate a few most popular channels, rather than intermediate popular ones. Reputation system can always well estimate all channels by using first hand and second hand observations. When “a” parameter is large e.g.1.5, there are only most popular channels and low popular ones, with only few intermediate popular ones. The network performance mostly depends on estimation of most popular channels. History-based rank performs as well as reputation system because it well estimates most popular channels. When “a” parameter decreases from 1.5 to 0.5, the number of intermediate popular channels increases while the number of most popular ones decreases. The network performance mostly depends on estimation of both most popular and intermediate popular channels. In this case, the performance of history-based rank becomes worse than reputation system since more intermediate popular channels cannot be accurately estimated due to the lack of popularity information using only direct observations. More intermediate channels get as few forwarding opportunities as low popular channels do, since they are estimated to be equally popular. On the other hand, the performance of reputation system is less sensitive to the "a" parameters, with only small performance decrease when "a" parameter becomes small. This is because: by taking account both direct observations and second hand observation, it can always well estimate both most popular channels and intermediate popular ones for any "a" parameters.

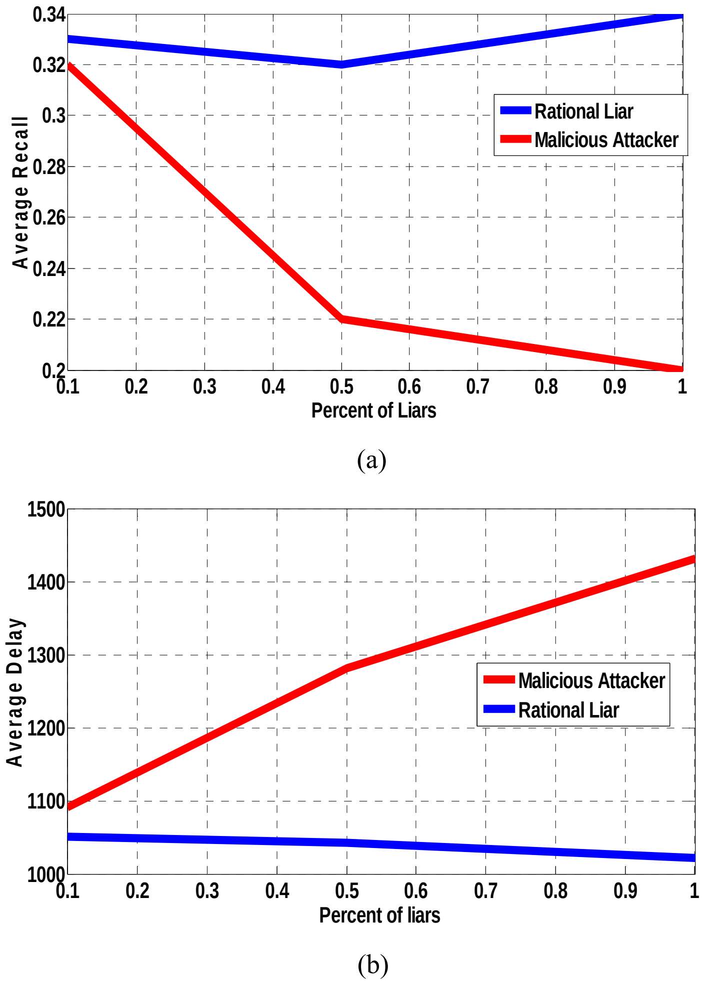


Figure 10: Study of impact of liar and malicious attacker on reputation system

In fig 10 (a) (b), we study the impact of liar and malicious attacker on reputation system. The deviation test threshold THS is set to 0.4. Two types of liars are considered: rational liars, malicious attackers. Firstly, the rational liars pass the fake reputation values of both its subscribed and published channels to its peers, so as to maximize its own benefit. The fake reputation values of channels are much larger than their real value. Secondly, the malicious attackers pass fake reputation value of all its forwarded channels (including its subscribed channels, its helped channels, and its published channel) to its peers to break down the network service. The fake reputation value is much lower than the real values of channels. From fig 10, it is shown that the performance of reputation system is robust against rational liars even when the 100% nodes are liars in terms of average delay and average recall. In contrast, it is prone to attackers as the percentage of liars increase, in terms of average delay and average recall. In the latter case, advanced security mechanism needs to be enhanced to prevent attackers. This is left for a future work.

5. Conclusion

We aim at designing a reputation-based content dissemination framework over human opportunistic network. Firstly, we propose and study various forwarding and public cache replacement heuristics under the ideal knowledge of channel popularity at each node. Simulation results show that when the number of channel is large, Most-Most schemes performs best, while Uniform-Uniform performs worst for both average recall and average delay; On the other hand, when the number of channel is small, the differences of various heuristics are minor. Secondly, there is a critical value of public cache size, below which network performance is limited by public cache size and network bandwidth (inter-contact time and contact time), above which network performance is limited by network bandwidth (inter-contact time and contact time). In latter case, network performance keeps constant even if the public cache size increases, because network bandwidth remains same. The above observations can also be found in the case of energy consumption per node for collaborative data dissemination. Both the observations on impact of public cache size and energy consumption counter indicates that the ad-hoc podcasting only needs a decent cooperation efforts from participating nodes to achieve best performance, because the bottleneck of the system is often the network bandwidth which is determined by node mobility and underlying link/physical layer, rather than cache size and energy consumption. Secondly, we propose a modified Bayesian framework based reputation system for estimate the channel popularity in a distributed way. By both first hand observations and the second hand observations shared with other nodes, node obtains the channel popularity information much faster and much more accurate. Simulation results show reputation system can always well estimate most popular, intermediate and low popular channels, compare to history-based rank which can only well estimate a few most popular channels. Reputation system significantly outperforms history-based rank when the public cache size is small (e.g. 5 chunks) or "a" parameter of Zipf-like distribution is small (e.g. between 0.5 and 1). Finally, we show system performance under the impact of two types of liars. It shows that our system is robust against arbitrary percent of rational liars, while the performance indeed suffers from malicious attackers. In the latter case, standard Bayesian framework using only the first hand information is preferred for estimating channel popularities.

For the future work, we plan to further investigate the performance of reputation system under more realistic mobility model or real mobility traces. We are also interested in analytically studying the optimal forwarding and caching schemes for ad-hoc podcasting over opportunistic network.

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Paper B

Optimal Channel Choices for Collaborative Ad-Hoc Dissemination

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Optimal Channel Choice for Collaborative Ad-Hoc Dissemination

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ABSTRACT

Collaborative ad-hoc dissemination of information has been proposed as an efficient means to disseminate information among nodes in a wireless ad hoc network. Nodes help in forwarding the information channels to the entire network, by disseminating the channels they subscribe to, plus others. We consider the case where nodes have a limited amount of storage that they are willing to devote to the public good, and thus have to decide which channels they are willing to help disseminate. We are interested in finding channel forwarder allocation strategies which minimize channel dissemination time. We first consider a simple model under the random mixing assumption; we show that channel dissemination time can be characterized in term of the number of nodes that forward this channel. Then we show that maximizing social welfare is equivalent to an assignment problem, whose solution can be obtained in a centralized way by the greedy algorithm. We show empirical evidence, based on Zune data, that there is a substantial difference between the utility of the optimal assignment and heuristics that were used in the past. We also show that the optimal assignment can be approximated in a distributed way by a Metropolis-Hastings sampling algorithm. We also give a variant that accounts for battery level. This leads to a practical channel selection and re-selection algorithm that can be implemented without any central control.

1. INTRODUCTION

Several applications relying on opportunistic data transfers between devices have been proposed recently. In [1], the authors propose a wireless ad-hoc podcasting system where in addition to downloading the content onto devices while docked to a desktop computer, the content is exchanged between devices while users are on the go. [1] proposes several heuristics for content exchange between devices based on the inferred preference of the user owning a device and that of encountered devices. Another related system is CarTorrent [2], a BitTorrent-style content dissemination system designed to exploit the wireless broadcast nature. The authors suggest various solicitation strategies which form the basis of their protocols.

We consider the scenarios where nodes are willing to devote some limited amount of their resources to help the content dissemination. Specifically, this amounts for each user to decide which channels to help disseminate, in addition to the subscribed ones. A channel is an abstraction for various information feeds that generate content recurrently over time with some rate. For example, a podcast feed is a channel as well as a profile page of an online social network application (e.g. Facebook or Twitter). While many such services can well be provisioned at mobile devices by accessing the cloud, it is still of interest to speed up the information dissemination by augmenting with the device-to-device information transfer. Efficient multi-channel information dissemination through infrastructure and multi-hop wireless transfer would well support various mobile content sharing applications, e.g. Serendipity [22], in particular, in environments where access to the cloud is intermittent either because of the lack of connectivity or access cost. It is also suitable in environments where cellular radio network becomes saturated when users generate content sharing or streaming is popular. In analogy to [1], in our ad-hoc dissemination paradigm, the information is disseminated by interest-based pull from peer node during pair-wise node meetings, rather than pushing information to all encounter nodes. During a node meeting, a node may retrieve content for a channel from a peer node, but it is not compulsory. Also, the nodes are only associated in a pair-wise manner, even if there are more neighbours within proximity. The reason is to maximize data exchanged during each node meeting, rather than maximizing network connectivity. We believe in most scenarios the number of information channels is so large that the users are only able or willing to help disseminating a limited subset of channels due to the resource constraints of the mobile device such as cache size, node meeting duration, or battery etc. This is indeed confirmed by real podcast subscription dataset Zune, where there are 8000+ podcast channels and each user subscribes 6 channels on average [4]. The constraint on the number of channels to help by a user, naturally translates to storage and energy constraints by this user. Indeed, the smaller the number of channels, the smaller the storage requirements and the smaller the energy consumption as there are fewer channels whose content needs to be synchronized at encounter of other user devices. We consider a setting where users are cooperative in optimizing the content dissemination, an assumption that underlies the prior work [1].

We are interested in finding channel selection strategies which optimize channel dissemination times with respect to a system welfare objective. The key assumption that facilitates our framework is that there is a relation between the channel dissemination time and the fraction of the nodes that forward the given channel. Such a relation can be obtained by modelling or empirical analysis, examples of which we show in this paper. However, in this paper we do not advocate any specific function to describe the relation between the dissemination time and the fraction of the forwarding nodes–a thorough analysis of this is left for future work. We cast the problem in the framework of system welfare optimization where the objective is to optimize an aggregate of the utility functions associated with individual channels. We show that, for a broad class of utility function, optimizing the social welfare is equivalent to an assignment problem whose solution can be obtained by a centralized greedy algorithm [3]. We show empirical evidence, based on real-world, large-scale data that contains information about the subscriptions of the Zune [4] users to audio podcasts, that there is a substantial difference between optimal assignment based on various utility functions and heuristics that were used in the past.

Then we consider the problem of defining a practical, distributed algorithm run by individual nodes to attain a given system objective. We show that the optimal assignment can be approximated in a distributed way by a Metropolis-Hastings sampling algorithm. The algorithm requires knowledge about the fractions of nodes subscribing or forwarding given channel which can be estimated based on local observations by each individual node. We also identify a class of Metropolis-Hastings algorithms that do not require any estimation. We show simulation results that demonstrate that our proposed distributed algorithms converge to the optimum points within the rates of convergence of interest in practice.

Our contributions can be summarized in the following points:

- We propose a framework for optimizing the dissemination of multiple information channels in wireless ad-hoc networks. The optimization is with respect to the dissemination times of individual channels subject to end-user resource capacity constraints. To the best of our knowledge, this is the first proposal for optimizing dissemination of multiple information channels in wireless-ad-hoc scenarios with respect to a well-defined global system objective.

- The framework enables a direct engineering by allowing derivation of algorithms that decide which channels are helped by which users so as to optimize a given system objective.
- The framework also allows a reverse engineering so that for some given channel selection algorithms used by individual nodes, we can determine which underlying global system objective is optimized.
- We show that an optimum system assignment of users to channels for forwarding can be found by a centralized greedy algorithm for a broad class of system objectives identified in this paper.
- Using the data about subscriptions of Zune users to audio podcast channels, we demonstrate that there exist scenarios where for given system objective, significant gains can be attained by system optimum assignment over heuristics suggested by previous work.
- We show that optimal system objective can be well approximated by a distributed algorithm based on Metropolis-Hastings sampling run by individual nodes, with only local observations.
- We show how to incorporate in our framework and algorithms the objective to optimize the battery expenditure.
- We present extensive simulation results that provide validation and practicality of the algorithms derived from our framework.

The paper is structured as follows. Section 2 introduces our system model and notation. Section 3 presents modelling and empirical analysis about the relation between the dissemination time of a channel and the fraction of the nodes that forward the channel. In this section, we also define the system objective and the utilities associated to the channel and provide some basic properties. Section 4 presents the system problem and the result that this problem can be solved by a centralized greedy algorithm. This section also contains characterization results of optimum assignment for a relaxed version of the system problem. Section 5 presents results on the gain of the system optimum based on the Zune data. Section 6 presents our Metropolis-Hastings algorithms. In Section 7 we show simulation results. Finally, related work is discussed in Section 8 and Section 9 concludes the paper.

2. SYSTEM MODEL AND NOTATION

We consider a system of N wireless nodes, or users, participating in the ad-hoc dissemination of J channels. We denote with U and J the sets of user and channels, respectively. Every node, say, u has a list $S(u)$ of subscribed channels. In the context of this study, we assume that $S(u)$ is fixed for every u. In contrast, every node maintains a variable list of helped channels, i.e. channels that this node keeps in its public cache in order to facilitate their dissemination. When two nodes meet, they update their cache contents. More precisely, if nodes u and u' meet, u gets from u' the content that is newer at u' for the channels that u either subscribes to or helps, and vice-versa. Thus, user pulls the new content from its peer purely based on user's own interests, rather than peer pushing all new content to the user. Node firstly updates the content of its subscribed channels from its peer encounter, and then updates the content of its helped channels from its peer encounter. The purpose is to give priority to user subscribed channels over helped channels. We also assume nodes only associate pair-wise even if there could be several neighbour nodes within proximity, in order to maximize the amount of data transferred during each node meeting. We do not account for the overhead of establishing contacts and negotiating content updates. We assume that when nodes meet the contact duration is large enough for all useful contents to be exchanged, i.e. we assume that the bottlenecks in the system performance are the disconnection times and cache content. In addition, we assume that, once in a while, a node gets direct contact to the Internet and downloads fresh content for the subscribed or helped channels.

At any given point in time, we call x the global system configuration, defined by

$$x_{u,j} = 1 \Leftrightarrow \text{node u subscribes to or helps channel } j$$

Let H (u, x) be the set of channels helped by node u when the configuration is x and let F (u, x) be the set of forwarded channels, i.e.

$$F(u, x) = H(u, x) \cup S(u), \; u \in U$$[5]

[5] In the following analysis, we assume Cu is always full.

We assume that every node u has a maximum cache capacity C_u (both private and public cache). To simplify, we count it in the number of channels each of which has one entry or chunk[6]. We assume that $C_u \geq |S(u)|$, i.e. every node can store all the subscribed channels. The configuration is thus constrained by

$$|F(u, x)| \leq C_u, \text{ for all } u \in U.$$

The problem is then to find a configuration x that satisfies these constraints and maximizes some appropriate performance objective, defined in the next section. Further, we want to find a method to approximate the optimal configuration in a fully distributed way.

We use the following notation:

$$s_j = \text{proportion of nodes that subscribe to channel } j$$

$$f_j(x) = \text{proportion of users that forward channel } j$$

$$= \frac{1}{N}\sum_{u \in U} x_{u,j}$$

Without loss of generality and unless indicated otherwise, we assume that channels are labelled in non-increasing order with respect to their subscription popularity, i.e. $s_1 \geq \cdots \geq s_J$. Also $\vec{s} = (s_1, \ldots, s_J)$ and $\vec{f} = (f_1, \ldots, f_J)$.

3. DISSEMINATION TIME AND UTILITY

To get a better handle on the performance objective we first use an epidemic style analysis, using ordinary differential equations.

3.1 Model-Based Dissemination Time

Consider a channel j and set the time origin to the time at which the most recent version was created by the source. We assume the configuration x is fixed and omit it from the notation in this section. Let $\sigma_j(t)$ be the proportion of j- subscribers that have received the most recent piece at time t, and let $\varphi_j(t)$ be the proportion of j-forwarders

[6] One information channel can have multiple entries. For the simplicity of our analysis, we assume each channel has one entry in our model

that have received the most recent piece at time t. Following epidemic modelling theory, for each channel j, nodes can be classified into four types: susceptible subscriber of channel j, infected subscriber of channel j, susceptible helper of channel j, and infected helper of channel j. In line with the definition in section 2, forwarders of channel j include both subscribers and helpers of channel j, e.g. susceptible forwarders of channel j = (susceptible subscribers + susceptible helpers) of channel j. The dynamics of the system can be described by the system of differential equations:

$$\frac{d}{dt}\sigma_j(t) = (\lambda_j + \eta\phi_j(t))(s_j - \sigma_j(t)) \qquad (1)$$

$$\frac{d}{dt}\phi_j(t) = (\lambda_j + \eta\phi_j(t))(f_j - \phi_j(t)) \qquad (2)$$

where λ_j is the contact rate between a node and an infrastructure that is able to deliver channel j (e.g. Access Points), and η is the contact rate between nodes. These equations correspond to the "random node mixing" assumption and are asymptotically valid when N is large. We assume Access Point stores all the data of all J channels.

$\frac{d}{dt}\sigma_j(t)$ is equal to the sum of the rate of susceptible subscribers of channel j meeting other infected forwarders of channel j and the rate of susceptible subscribers of channel j meeting the Access Points.

$\frac{d}{dt}\phi_j(t)$ is equal to the sum of the rate of susceptible forwarders of channel j meeting other infected forwarders of channel j and the rate of susceptible forwarders of channel j meeting the Access Points.

It follows that:

$$\frac{d\sigma_j}{d\phi_j} = \frac{s_j - \sigma_j}{f_j - \phi_j} \qquad (3)$$

Hence

$$\sigma_j(t) = \frac{f_j\sigma_j(0) - s_j\phi_j(0)}{f_j - \phi_j(0)} + \frac{s_j - \sigma_j(0)}{f_j - \phi_j(0)}\phi_j(t) \qquad (4)$$

We can solve Eq.(2) explicitly. Note that

$$\frac{1}{(\lambda + \eta\phi)(f - \phi)} = \frac{1}{\lambda + f}\left(\frac{1}{\lambda + \eta\phi} + \frac{1}{f - \phi}\right) \qquad (5)$$

from where we get

$$\phi_j(t) = \frac{1}{\eta}\left(-\lambda_j + \frac{(\lambda_j + \eta\phi_j(0))(\lambda_j + f_j\eta)}{\lambda_j + \eta\phi_j(0) + \eta(f_j - \phi_j(0))e^{-(\eta f_j + \lambda_j)t}}\right)$$

By Eq.(4) we obtain

$$\sigma_j(t) = \sigma_j(0) + (s_j - \sigma_j(0)) \times \frac{(\lambda_j + \eta\phi_j(0))(1 - e^{-(\eta f_j + \lambda_j)t})}{\lambda_j + \eta\phi_j(0) + \eta(f_j - \phi_j(0))e^{-(\eta f_j + \lambda_j)t}}. \quad (6)$$

Dissemination Time

Say that at time T_0 a chunk is issued by the source. Let T_1 be the time at which a proportion α of the subscribers have received this chunk. We call $t_j = T_1 - T_0$ the dissemination time and take it as metric for channel j.[7]

We compute t_j as follows. First note, from Eq.(6):

$$e^{-(\eta f_j + \lambda_j)t_j} = \frac{(\lambda_j + \eta\phi_j(0)(1 - K_j)}{\eta f_j K_j + \lambda_j + \phi_j(0)\eta(1 - K_j)}$$

where

$$K_j = \frac{\alpha - \frac{\sigma_j(0)}{s_j}}{1 - \frac{\sigma_j(0)}{s_j}}.$$

It follows

$$t_j = \frac{1}{\lambda_j + f_j\eta} \ln \frac{(f_j - \phi_j(0))\eta K_j + \lambda_j + \eta\phi_j(0)}{(\lambda_j + \eta\phi_j(0))(1 - K_j)}. \quad (7)$$

PROPOSITION 3.1. The dissemination time t_j is a monotonic non-increasing, strictly convex function of f_j.

Proof is in our technical report [23].

Of particular interest is the small injection rate regime, where dissemination is dominated by epidemic content. In this case we have

$$\begin{aligned} \sigma_j(0) &\ll \tfrac{\lambda_j}{\eta} \ll s_j \\ \phi_j(0) &\ll \tfrac{\lambda_j}{\eta} \ll f_j \end{aligned}$$

and Eq.(7) becomes

[7] This ODE formulation only considers dissemination of one chunk per channel, not multiple chunks per channel.

$$t_{\jmath} \approx \frac{1}{\eta f_{\jmath}} \left(\ln \frac{\alpha}{1-\alpha} + \ln \frac{\eta f_{\jmath}}{\lambda_{\jmath}} \right). \qquad (8)$$

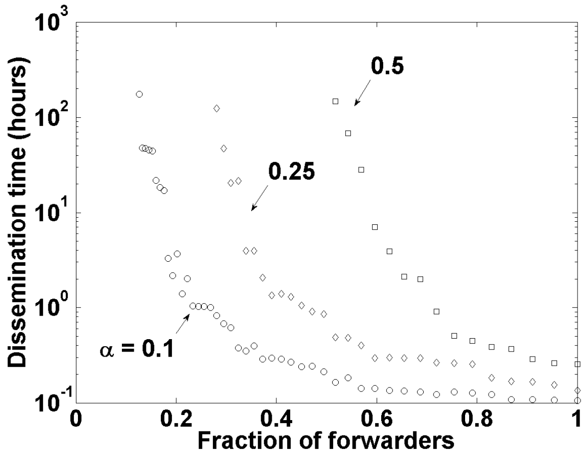


Figure 1: Dissemination time versus the fraction of forwarding nodes in CAM data. Each mark shows the median value of the dissemination time obtained by taking each node as a source and repeating for 10 random elections of the forwarding nodes.

3.2 Empirical Dissemination Time

We consider the dissemination time evaluated by using real mobility traces. In particular, we consider (CAM) a data trace of mobility of humans in the Cambridge (UK) area [5] and (SF-TAXI) a data trace of taxi routes in the San Francisco area [6]. CAM dataset contains information about the contacts between human-carried Bluetooth-equipped devices of about 40 users over more than 10 days. SF-TAXI contains the GPS coordinates for each of about 500 taxis over a month period. We define a contact between two nodes in the SF-TAXI trace as any instance in the trace if the distance between the nodes is smaller or equal to 500 meters [7].

We infer the dissemination time by conducting the following experiment. For given data trace (either CAM or SF-TAXI), we fix a portion of forwarders picked uniformly at random from all the nodes. At an instant of time, we inject a message to one of the forwarders and then pass onwards in time through the trace recording the instances at which a forwarder first received the message by encountering a forwarder that has already received the message. For the CAM data, we repeat the experiment for each source and 10 random samples for the set of designated forwarders. Finally, for each given portion of forwarding nodes, we compute the median dissemination time.

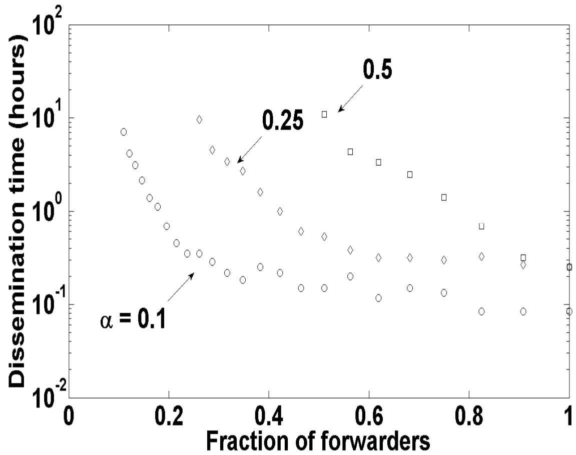


Figure 2: Same as in Figure 1 but for SF-TAXI data.

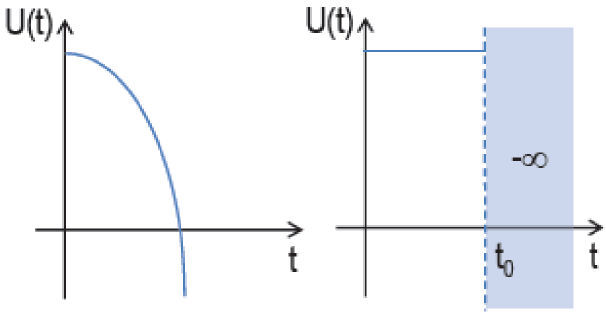


Figure 3: Utility of the dissemination time. (Left) A concave decreasing utility with respect to the dissemination capturing the increasing rate of user unhappiness as the dissemination time increases. (Right) Finite utility up to some given dissemination time t_0 and $-\infty$ utility for the dissemination time larger than t_0

Fig.1 and Fig.2 show the empirical dissemination time versus the portion of forwarding nodes for the CAM and SF-TAXI traces, respectively. In both cases, they confirm that the dissemination time is well fitted by a curve that exhibits diminishing returns for large values of the portion of forwarders.

3.3 Utility Function

We assume that for each channel there is an underlying utility function $U_j(t_j)$ that specifies the satisfaction of a subscriber for channel j with the dissemination time t_j. It is natural to assume that $U_j(t_j)$ is a non-increasing function of t_j. We will discuss later in this section some additional properties that appear natural for the utility $U_j(t_j)$ function to satisfy.

We denote with $V_j(f_j) = U_j(t_j(f_j))$ the utility function for channel j with respect to the fraction of users who forward channel j. It is natural to assume that $V_j(f_j)$ is a monotonic non-decreasing function of f_j. This indeed follows, if both $U_j(t_j)$ and $t_j(f_j)$ are non-increasing functions which are rather natural assumptions.

It remains to discuss what the system welfare utility is, i.e. when considering all channels together. We admit standard definition that the system welfare is a weighted sum of the utilities over all channels, i.e. for given positive weights $\vec{w} = (w_1, \ldots, w_J)$,

$$V(\vec{f}) = \sum_{j \in \mathcal{J}} w_j V_j(f_j).$$

Two special cases may be of interest, which correspond to different fairness objectives. The former is channel centric, in that it considers each channel as one entity, regardless of the number of subscribers. This utility is obtained by setting all the weights w_j to 1, hence we have

$$V_{CH}(\vec{f}) = \sum_{j \in \mathcal{J}} V_j(f_j) \tag{9}$$

where V_j is a per-channel metric, for example as in Eq. (7) or Eq.(8).

The latter is user centric and has the weights such that w_j is proportional to the proportion of subscribers s_j, hence we consider

$$V_{US}(\vec{f}) = \sum_{j \in \mathcal{J}} s_j V_j(f_j) \tag{10}$$

with V_j as before.

In Section 6 we will show that this utility framework can easily be extended to battery saving.

Sufficient Conditions for Concave Utility

We discuss a set of sufficient conditions that ensure that the utility $V_j(f_j)$ is a concave function of f_j. This class of utility functions ensures uniqueness of the solution to the system welfare problem that we consider in Section 4.1.

PROPOSITION 3.2. Suppose (C1) $U_j(t_j)$ is a non-increasing, concave function of t_j and (C2) $t_j(f_j)$ is a convex function of f_j. Then $V_j(f_j)$ is a concave function of f_j .

PROOF: By simple differential calculus,

$$\begin{aligned} V_j'(f_j) &= U_j'(t_j)t_j'(f_j) \\ V_j''(f_j) &= U_j''(t_j)\left(t_j'(f_j)\right)^2 + U_j'(t_j)t_j''(f_j). \end{aligned}$$

From the last equation, (C1) $U_j'(t_j) \le 0$, $U_j''(t_j) \le 0$, and (C2) $t_j''(f_j) \ge 0$, it follows $V_j''(f_j) \le 0$, i.e. $V_j(f_j)$ is a concave function of f_j. □

Condition (C1) says that the utility function $U_j(t_j)$ captures the increasing dissatisfaction of a subscriber of channel j with the dissemination t_j. See Figure 3–left for an illustration. Such a utility function could be seen as a smooth version of a step function (see Figure 3-right) where the utility $U_j(t_j)$ is finite up to some threshold dissemination time and becomes $-\infty$ for larger dissemination times. This captures a scenario where a channel subscriber values the information of this channel if received within some time, and otherwise considers it virtually useless.

Condition (C2) says that the dissemination time $t_j(f_j)$ exhibits diminishing returns with increasing portion of forwarders f_j. We have already demonstrated cases in Section 3.1 and Section 3.2 that support this assumption.

4. SYSTEM WELFARE PROBLEM

4.1 The Greedy Algorithm

We pose a system welfare problem where the objective is to optimize the aggregate utility of the dissemination times of individual channels subject to the end-user capacity constraints. Solving the system welfare problem amounts to finding an assignment of users to channels that solves the following problem:

$$
\begin{array}{ll}
\text{SYSTEM} & \\
\text{maximize} & \sum_{j=1}^{J} w_j V_j \left(\frac{1}{N}\sum_{u=1}^{N} x_{u,j}\right) \\
\text{over} & x_{u,j} \in \{0,1\} \\
\text{subject to} & \sum_{j=1}^{J} x_{u,j} \le C_u \\
 & x_{u,j} = 1, (u,j) : j \in F(u)
\end{array}
$$

Defining the system welfare utility as an aggregate of individual utilities is rather standard in the microeconomics framework of the resource allocation and was successfully applied in the contexts of wireline Internet [8] and wireless networks [9]. Note that in SYSTEM, w_j are positive constants that can be arbitrarily fixed. In particular, it is of interest to define w_j to be proportional the portion of users subscribed to channel j (i.e. s_j). In this case, the utility $v_j()$ can be interpreted as the utility for channel j for a typical subscriber of channel j.

We rephrase the SYSTEM problem as an optimization over the number of helper user per channel. Consider $\vec{H} = (H_1, \ldots, H_J)$ where H_j is the number of helper users for channel j. Let us define v(A) for $A \subseteq J$, by

$$v(A) = \sum_{u \in \mathcal{U}} \min\left(\sum_{j \in A} 1_{j \in \mathcal{J} \setminus S(u)}, C_u - |S(u)|\right). \quad (11)$$

Let P (v) be the polyhedron defined by

$$P(v) = \{x \in N^J : x(A) \le v(A), A \subseteq J\}.$$

We consider the following problem:

SYSTEM-H

$$\begin{array}{ll} \text{maximize} & \sum_{j=1}^{J} w_j V_j \left(s_j + \frac{1}{N} H_j \right) \\ \text{over} & \vec{H} \in P(v). \end{array}$$

PROPOSITION 4.1. *The optimal value of the solution of SYSTEM is equal to that of SYSTEM*-H.

Proof:

Proof is based on a reduction to a max-flow problem and is available in [23].

We denote with $\Delta_j V(\vec{s} + \vec{H}/N)$ the increment of the aggregate utility function by assigning a user to channel j, i.e.

$$\begin{aligned} & \Delta_j V(\vec{s} + \vec{H}/N) \\ = \; & V(\vec{s} + (\vec{H} + e_j)/N) - V(\vec{s} + \vec{H}/N) \\ = \; & w_j \left[V_j(s_j + (H_j + 1)/N) - V_j(s_j + H_j/N) \right] \end{aligned}$$

where e_j is a vector of dimension $|J|$ with all coordinates equal to 0 but the j th coordinate equal to 1.

Algorithm 1 Centralized GREEDY Algorithm for Allocation of Helped Channels.

```
H = 0
while 1 do
    Find I ∈ 𝒥 such that H⃗ + e_I ∈ P(v)
    and Δ_I V(s⃗ + H⃗/N) ≥ Δ_j V(s⃗ + H⃗/N) for all j ∈ 𝒥
    such that H⃗ + e_j ∈ P(v)

    if there exists no such I then break
    end if
    H_I ← H_I + 1
end while
```

Proof: Under the assumption that $V_j(x)$ is a concave function with respect to x we have that $V_j(s_j + x)$ is a concave function with respect to x. Showing in addition that P (v) is a submodular polyhedron, we verify the assumptions of Corollary 1 in Feedergruen and Groenevelt [3] from which the asserted result follows.

A polyhedron P (v) is submodular if and only if v( ) is a submodular function, i.e.

$$v(A \cup B) + v(A \cap B) \leq v(A) + v(B), \quad A, B \subseteq J . \qquad (12)$$

But this follows from the fact that v() is the characteristic function of the graph in Figure 4 and [11, Lemma 3.2].

4.2 Particular Channel Choice Schemes

In this section, we introduce three particular channel selection strategies. Under the assumption of random mixing, the first two correspond to centralized version of uniform and most solicited strategies in [1]. The third strategy is new and arises from the Metropolis sampling in sec.6.

4.2.1 Uniform

Under the uniform channel choice, each user u picks a subset of $C_u - |S(u)|$ channels by sampling uniformly at random from the set of channels that user u is not subscribed to, i.e. from the set of channels $J \setminus$ S(u).

The uniform channel assignment biases the assignment in the following way – the mean portion of users who help a channel j is given by:

$$\begin{aligned} h_j &= \frac{1}{N}\sum_{u=1}^{N} \frac{C_u - |S(u)|}{J - |S(u)|} 1_{j \in \mathcal{J} \setminus S(u)} \\ &= (1 - s_j)\mathbb{E}\left(\frac{C_U - |S(U)|}{J - |S(U)|} | j \in S(U)\right) \end{aligned}$$

where U denotes a user picked uniformly at random from the entire population of users.

In the special case of symmetric users so that $C_u = c \bullet N$ and $|S(u)| = s \bullet N$ for each user u, we have $h_j = (1 - s_j)\dfrac{c - s}{J - s}$. Furthermore, if the number of distinct channels in the entire system is much larger than the number of channels subscribed by any user, i.e. J >> $|S(u)|$ for each user u, then $h_j \approx (1 - s_j)\dfrac{c - s}{J}$. In such cases, we note that the uniform channel assignment biases towards helping less popular channels.

4.2.2 Top Popular

Under the top popular channel assignment, each user u picks channels from the set of channels J \ S(u) without replacement in the decreasing order of the channel subscription popularity and random tie break until $C_u - |S(u)|$ channels are picked or there are no channels left. This is a greedy scheme that favours popular channels. We consider this scheme in the numerical evaluations in Sec.5.

4.2.3 Pick from a Neighbour

We consider channel selection strategies under which each user *u* upon encountering another user *u0* picks a candidate channel from the user *u0* and then based on some decision process decides whether to replace a channel to which user *u* currently helps with the candidate channel. The decision process is assumed to be local, independent of the current assignment of users to channels, which makes these strategies of quite practical interest.

We will construct one such a scheme, in Sec. 6, based on the Metropolis-Hastings sampling. We will see that such a scheme is associated with a system welfare problem with the following objective function:

$$V_{PFN}(\vec{f}) = \sum_{j \in \mathcal{J}} V_j^{PFN}(f_j)$$

with

$$V_j^{PFN}(f_j) = (\alpha_j + C) f_j + D f_j \ln f_j \qquad (13)$$

where *C* and *D* are system constants and $\alpha_j \geq 0$ is a constant for channel *j*, which expresses its relative importance (the higher the α_j , the more important the channel *j*).

The function $V_j^{PFN}(f_j)$ in Eq. (13) is a monotonic nondecreasing function of f_j. Note, however, that $V_j^{PFN}(f_j)$ is a convex function of f_j. It is thus not concave and hence does not validate the condition discussed in Sec. 3.3, which ensures optimality of the greedy assignment in Sec. 4.1. Moreover, note that $U_j^{PFN}(t_j(f_j)) = V_j^{PFN}(f_j)$ is not a concave function of the dissemination time t_j .

5. SYSTEM OPTIMUM VS. HEURISTICS

In this section, we demonstrate:

> A system optimal assignment of channels can yield significantly larger system welfare than some heuristics suggested by prior work.

In particular, we compare with the Uniform and Top Popular assignments defined in the preceding section.

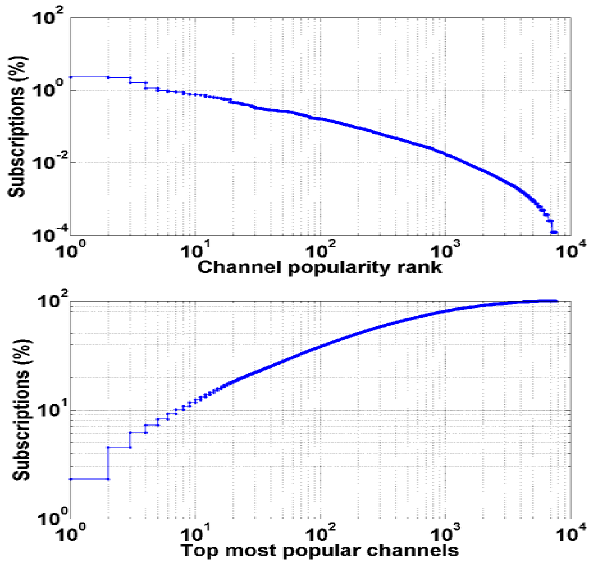


Figure 5: Channel subscription popularity from the Zune podcasts data. (Top) Fraction of the subscriptions per channel. (Bottom) Fraction of the subscriptions over a set of most popular channels. The channels identifiers are sorted in decreasing order with respect to the number of subscriptions.

We use the subscription assignments of users to channels that we derive from the subscriptions of the users of Zune to audio podcast feeds. This dataset consists of 8,000+ distinct podcast feeds and more than a million of users. The data provides us with complete information users' subscriptions to channels. In Figure 5-top, we show the fraction of subscriptions covered by individual channels. This metric corresponds to our definition of $\vec{s}$. We note that the distribution is quite skewed with a few channels with many subscriptions and many with a few. The median number of fraction of subscriptions per channel is as small as about $2*10^{-5}$. Moreover, only about 1% of all the channels have the fraction of subscriptions at least the factor 1/10 of that of the most popular channel. The body of the distribution in Figure 5–top is well approximated by a line (power-law) with the slope of about 2/3. In Figure 5-bottom, we re-plot the same data but show the fraction of the subscriptions covered by a set of most popular channels. From this figure we note that half of the subscriptions are covered by as few as 2.5% of the most popular channels.

We consider the channel-centric system welfare defined by the utility functions $V_j(f_j) = -t_j(f_j)$ where $t_j(f)$ is the dissemination time given by Eq.(7). For each user u, we set $C_u = S(u) + C$ where S(u) is specified by the input data and C is a parameter which is the size if the cache that node contribute for helping dissemination of other channels. We compute optimum assignment by using the algorithm GREEDY (Sec.4.1). Uniform and Top Popular assignments are computed as prescribed by their respective definitions.

In Figure 6 we show the dissemination time per subscription versus the per node capacity C. The rate of the access to the infrastructure is fixed to 1 access per day by each user. The rate at which each user encounters other users is fixed to 100 users per day. If the dissemination is solely by direct access to the infrastructure, then the mean delay is about 13.5 hours. We note that the mean delay under the system optimum assignment can be reduced by the order of several hours if the dissemination is augmented with the peer-to-peer dissemination. Perhaps even more interesting, we observe that the gap between the system optimum and that of Uniform and Top Popular assignments can be significant.

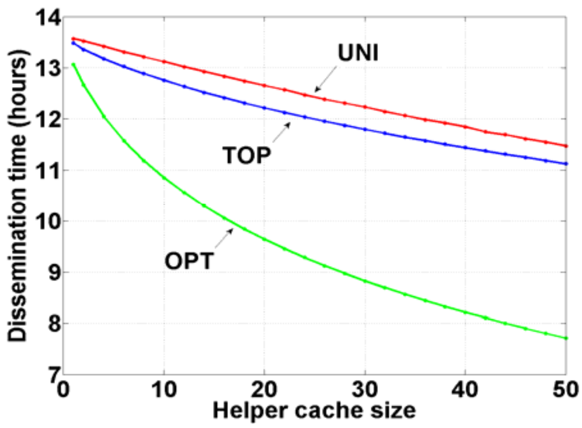


Figure 6: Dissemination time per subscription versus the size of the public cache C, C_u = |S(u)| + C.

In Figure 7 we present the results under the same setting as in Figure 6 but for varying the encounter rate and holding the cache size C fixed to 5 (Top) and 20 (Bottom). These results show lack of order for the Uniform and Top Popular assignments – for some cases one is better than the other one and vice-versa for other cases. In any case, system optimum indeed provides best performance.

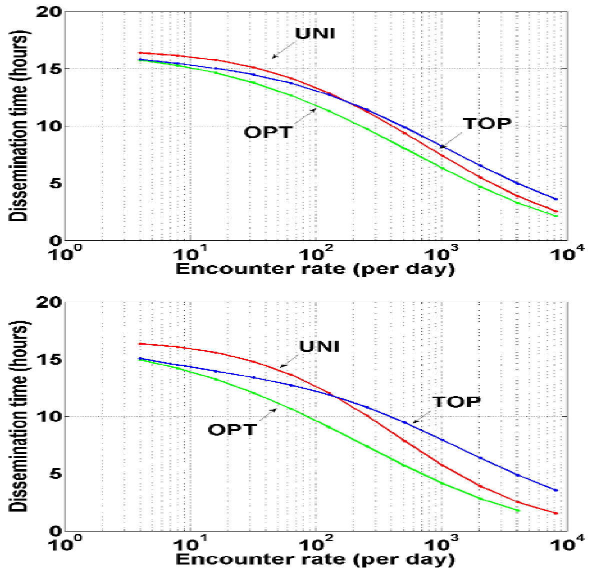


Figure 7: Dissemination time per subscription versus the rate of encounters η. The cache for user u set as C_u = S(u) + C with (Top) C = 5 and (Bottom) C = 20.

6. A DISTRIBUTED METROPOLIS HASTINGS ALGORITHM

We now consider the problem of designing a distributed algorithm. The goal is for each node to control its set of helped channels so that the resulting global configuration x maximizes a global utility function of the form

$$V(x) = \sum_{j \in \mathcal{J}} w_j V_j(f_j(x)) \qquad (14)$$

as discussed in Section 3 (note that, unlike in Section 3, we make the dependence on the global configuration x explicit).

6.1 Metropolis-Hastings

We propose to use a Metropolis-Hastings algorithm [13], as it lends itself well to distributed optimization, and were successfully used in distributed control problems in wireless networks [14]. Before giving our distributed algorithm, we first give a short description of a centralized version of the Metropolis Hastings algorithms.

At every time step, the algorithm picks a tentative configuration x', with probability Q(x, x'), where x is the current configuration. We assume that matrix Q(x, x') has the weak symmetry property:

$$Q(x, x') > 0 \Rightarrow Q(x', x) > 0$$

for all $x \neq x'$. The tentative configuration is accepted (i.e. becomes the new configuration) with probability p = min (1, q) with

$$q = \frac{\pi(x')Q(x', x)}{\pi(x)Q(x, x')} \qquad (15)$$

where $\pi(\cdot)$ is a probability distribution on the set of possible configurations. The algorithm does not converge in its strict sense, however, after a large number of iterations, the probability distribution of the configuration x converges to the a priori distribution $\pi(\cdot)$. Typically, one uses for $\pi(\cdot)$ a Gibbs distribution, given by

$$\pi(x) = \frac{1}{Z} e^{\frac{V(x)}{T}} \qquad (16)$$

where T is a system parameter (the "temperature") and Z is some normalizing constant. If T is small, the distribution $\pi(\cdot)$ is very much concentrated on the large values of V(x), so that the algorithm produces random configurations that tend to maximize V(x).

6.2 A Distributed Rewiring Algorithm

We use Metropolis-Hastings as follows. We use a Gibbs distribution, as in Eq.(16) with $V(\cdot)$ the utility function in Eq.(14). We consider every meeting between two nodes as one step of the algorithm. When two nodes meet, they opportunistically exchange content updates; then one of them, say u is selected as leader and attempts to replace one of its helped channels by one channel forwarded from the set held by the other node, say v, as described in Algorithm 2.

We now turn to the computation of the acceptance probability (line 5 of the algorithm), as given by Eq.(16). First we compute $Q(x, x')$ where $x' = x - 1^{u,j} + 1^{u,j'}$ is the new configuration ($1^{u,j}$ is the configuration vector defined by $1^{u,j}_{u',j'} = 1$, if u = u' and j = j', 0 otherwise):

Algorithm 2 Distributed Algorithm for Allocation of Helped Channels

if $F(u,x) \subset F(v,x)$ **then** do nothing
else
  u selects one channel j uniformly at random in the set $H(u,x)$
  u selects one channel j' uniformly at random in the set $F(v,x) \setminus F(u,x)$
  compute the acceptance probability $p = \min(1,q)$ with q given by Eq.(19)
  draw a random number U uniformly in $[0;1]$;
  if $U < p$ **then** drop channel j and adopt channel j' as a helped channel
  end if
end if

PROPOSITION 6.1. The following holds

$$\frac{Q(x',x)}{Q(x,x')} = \frac{\sum_{v \neq u} \frac{1_{j \in F(v,x)}}{|F(v,x) \setminus F(u,x)| + 1_{j' \notin F(v,x)}}}{\sum_{v \neq u} \frac{1_{j' \in F(v,x)}}{|F(v,x) \setminus F(u,x)|}}. \quad (17)$$

Proof can be found in our technical report [23] [8].

We will make use of the following approximation. Proof can be found in our technical report [23].

$$\frac{Q(x',x)}{Q(x,x')} \approx \frac{f_j(x)}{f'_j(x)}. \quad (18)$$

We also note the following result (Proof in the appendix of [23]):

PROPOSITION 6.2. Suppose that for a finite constant D > 0, $\lim_{N \to +\infty} N \bullet T = D$. Then

$$\lim_{N \to +\infty} \frac{V(x') - V(x)}{T} = \frac{1}{D} \left(w_{j'} V'_{j'}(f_{j'}(x)) - w_j V'_j(f_j(x)) \right).$$

In view of the last proposition, we have

---

[8] Equations (17) (18) does not represent my opinions, but only opinions from MV and JY. In fact, I do not quite understand the proof of (17) and (18). I have made another formulation of MH.

$$
\begin{aligned}
q &= \frac{Q(x',x)}{Q(x,x')} e^{\frac{1}{T}\left(V(x')-V(x)\right)} \\
&\approx \frac{Q(x',x)}{Q(x,x')} e^{\frac{1}{NT}\left(w_{j'}V'_{j'}(f_{j'}(x))-w_jV'_j(f_j(x))\right)}.
\end{aligned}
$$

Combing with (18) we obtain for q the value

$$q = \frac{f_j(x)}{f_{j'}(x)} e^{\frac{1}{D}\left(w_{j'}V'_{j'}(f_{j'}(x))-w_jV'_j(f_j(x))\right)} \tag{19}$$

where D = NT is a global system parameter.

Algorithm 2 requires node u to estimate f_j and $f_{j'}$. This can be done by having node exchange, when they meet, updates of channel popularity for all channels that they know of, and then performing exponential smoothing. A simple scheme is as follows. Every node u maintains for every channel j an estimate $\hat{f}_j$. When node u meets node u', for all channels that u' helps or subscribes to, node u does $\hat{f}_j \leftarrow$ a + (1-a) $\hat{f}_j$ and for all other channels $\hat{f}_j \leftarrow$(1-a) $\hat{f}_j$ where 0<a<1.

Further, all nodes need to share the global system variable D, and know the utility function of each channel (the latter can be contained as meta-information in the channel data).

6.3 A Simplified Algorithm

It is possible to entirely avoid the estimation of the f_j quantities, albeit at the expense of imposing a family of utility functions. The idea is to pick a set of utility functions $V_j(\cdot)$ such that f_j and $f_{j'}$ cancel out in Eq.(19). This results in a scheme that belongs to the class of schemes pick from neighbor that was introduced in Section 4.2.3.

THEOREM 6.1 If for each channel j, the utility function is $V_j^{PFN}(\cdot)$ in Eq.(13) then q in Eq.(19) is given by:

$$q = \frac{\beta_{j'}}{\beta_j} \tag{20}$$

with $\beta_j = e^{\frac{\alpha_j}{D}}$ and $\beta_{j'} = e^{\frac{\alpha_{j'}}{D}}$. In particular, q is thus independent of $f_j(x)$, $f_{j'}(x)$ and more generally of the configuration x.

Proof: Follows from Eq.(13) and Eq.(19)

With this simplified algorithm, nodes need to know the static parameters $\beta_j > 0$ associated with each channel. There is no global constant, nor is it necessary to evaluate $f_j(x)$. Higher values of j mean that we give more value to disseminating channel j more quickly. Note that only the relative values of β_j matter, as Eq.(20) uses only ratios, and β_j can thus be interpreted as the priority level for channel j. The resulting algorithm is as follows:

Algorithm 3 Distributed Algorithm for Allocation of Helped Channels when Utility is Given by Eq.(13). Every channel j has a static priority level $\beta_j > 0$.

if $F(u,x) \subset F(v,x)$ **then** do nothing
else
    u selects one channel j uniformly at random in the set $H(u,x)$
    u selects one channel j' uniformly at random in the set $F(v,x) \setminus F(u,x)$
    if $\beta_{j'} \geq \beta_j$ **then** drop channel j and adopt channel j' as a helped channel
    else
        draw a random number U uniformly in $[0;1]$;
        if $U < \frac{\beta_{j'}}{\beta_j}$ **then** drop channel j and adopt channel j' as a helped channel
        end if
    end if
end if

If we set $\beta_j = 1$ for all channels, i.e. we give all channels the same utility function, then Algorithm 3 always accepts the proposed change. Note however that, even in this case, the resulting allocation is, in general, not uniform, as the optimal allocation depends on the proportion of subscribers s_j for each channel; indeed, the algorithm will tend to give more help to channels that have few subscribers. Note also that, in general, the scheme is different from that in Sec. 4.2.1 as under the scheme therein, each user picks from the set of all distinct channels for which this user is not a subscriber, while for the algorithm in the present section, the picking is from the forwarding channels of an encountered user. So the channel pick-up is from local channels at both two encounter nodes.

6.4 A Battery Saving Algorithm

The previous algorithm may be improved to account for battery saving. The motivation is that a node may be reluctant to exchange helped channels if its battery level is low.

We address this issue as follows. Assume that every node u knows its battery level $b_u \geq 0$. The battery is empty when $b_u = 0$. Assume to simplify that all nodes measure b_u in the same scale, for example, number of remaining hours of operation at full activity. We can replace the global utility in Eq.(14) by

$$\sum_{j \in \mathcal{J}} w_j V_j(f_j) - \sum_{u \in \mathcal{U}} W_u(b_u)$$

where $W_u()$ is a convex, decreasing function of its argument (for example $W_u(b) = \frac{1}{b^m}$), such that $W_u(b)$ expresses the penalty perceived by user u when its battery level is b. We can apply the Metropolis-Hastings algorithm with this new function. The only difference is in the computation of the acceptance probability. This can be applied to Algorithms 2 or 3 in the same way, we give the details only for Algorithm 3. The computation of q in Eq.(20) is replaced by

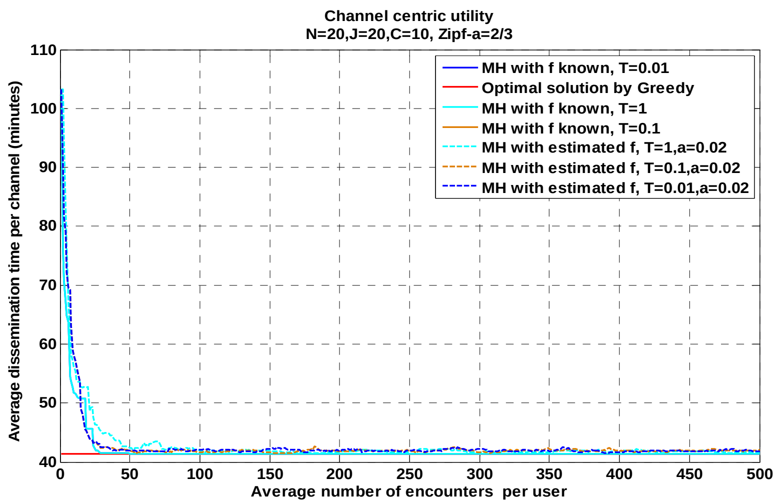
$$q = \frac{\beta_{j'}}{\beta_j} e^{-[h_u(b_u) - h_{u'}(b_{u'})]} \qquad (21)$$

where u and u' are the two nodes involved in the interaction and $h_u(b) > 0$ is the marginal cost of exchanging a channel when two nodes meet, divided by the temperature T (an increasing function of b). The resulting algorithm is the same as Algorithm 2 with Eq.(19) on line 5 replaced by Eq.(21). The required configuration is (1) every channel j has a static priority level $\beta_j > 0$ and (2) every node u knows its own function h_u(b) for the cost of exchanging one channel with a neighbor when this node's battery level is b.

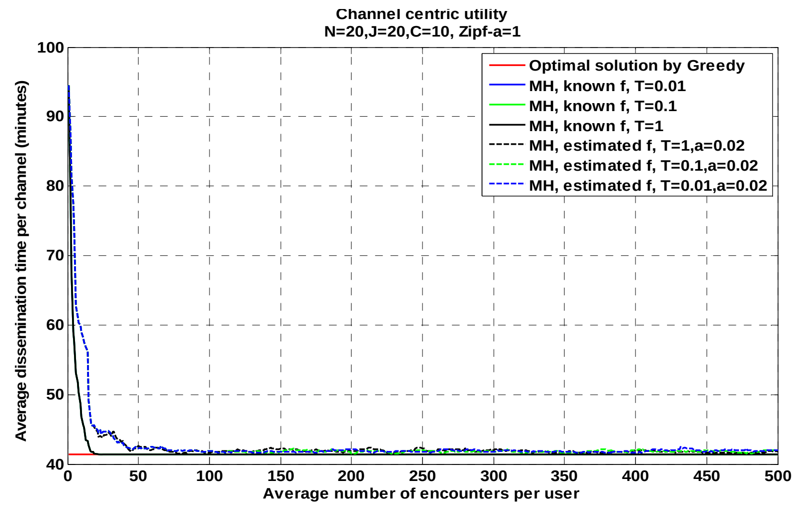
7. SIMULATION RESULTS

In this section, we present simulation results with the following goals: (i) demonstrate concentration of the distributed Metropolis-Hastings algorithm to the optimum system welfare and (ii) demonstrate that optimizing system welfare under real-world mobility produces better forwarding assignments of channels over other heuristics. We used our own discrete-event simulator in C++.

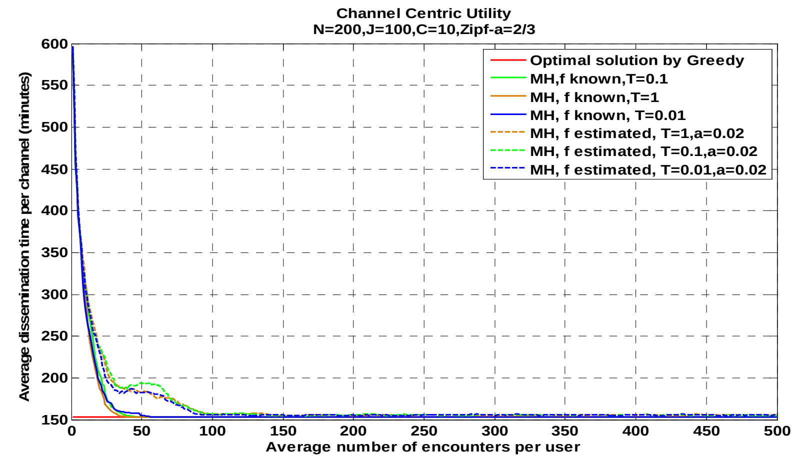
For the first goal, in order to cover a broad set of parameters, we conducted simulations by varying the parameters along the following dimensions: (i) small and large system scale with respect to the number of users and the number of channels, (ii) different distributions for the subscriptions per channel, (iii) the fractions of nodes forwarding or subscribed to a channel either known or estimated online, and (iv) a range of the temperatures for the Metropolis-Hastings algorithm. Specifically, we consider the random mixing mobility in order to provide results for scenarios for which we have good understanding of the relation between the channel dissemination time and the fraction of the forwarding nodes. For the second goal, we conducted simulations over real mobility trace by varying the parameters along the following dimensions: (i) small and large cache size; (ii) small number of channels and large number of channels



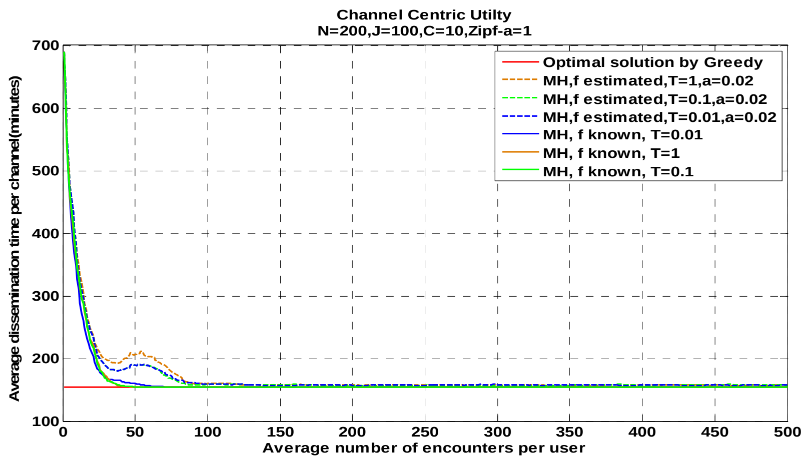
8 (a)


Channel centric utility
N=20,J=20,C=10, Zipf-a=1
Optimal solution by Greedy
MH, known f, T=0.01
MH, known f, T=0.1
MH, known f, T=1
MH, estimated f, T=1,a=0.02
MH, estimated f, T=0.1,a=0.02
MH, estimated f, T=0.01,a=0.02
Average dissemination time per channel (minutes)
Average number of encounters per user

8 (b)


Channel Centric Utility
N=200,J=100,C=10,Zipf-a=2/3
Optimal solution by Greedy
MH,f known,T=0.1
MH, f known,T=1
MH, f known, T=0.01
MH, f estimated, T=1,a=0.02
MH, f estimated, T=0.1,a=0.02
MH, f estimated, T=0.01,a=0.02
Average dissemination time per channel (minutes)
Average number of encounters per user

8 (c)


Channel Centric Utilty
N=200,J=100,C=10,Zipf-a=1
Optimal solution by Greedy
MH,f estimated,T=1,a=0.02
MH,f estimated,T=0.1,a=0.02
MH,f estimated,T=0.01,a=0.02
MH, f known, T=0.01
MH, f known, T=1
MH, f known, T=0.1
Average dissemination time per channel(minutes)
Average number of encounters per user

8 (d)

Figure 8: Convergence of the Metropolis-Hasting (MH) algorithm under channel centric system welfare: (a) small scale, Zipf-2/3, (b) small-scale, Zipf-1, (c) large-scale, Zipf-2/3, (d) large scale, Zipf-1. Small-scale refers to (N,J) = (20, 20) and the large-scale refers to (N,J) = (200, 100). The y-axis is the mean dissemination time over all channels. The thick horizontal line denotes the system optimum mean dissemination time. Other solid curves denote the mean dissemination time obtained with the Metropolis-Hasting algorithm with the portion of nodes that forward any given channel known ($\vec{f}$). The dashed lines denote the same but with $\vec{f}$ locally estimated.

7.1 Random Mixing Mobility

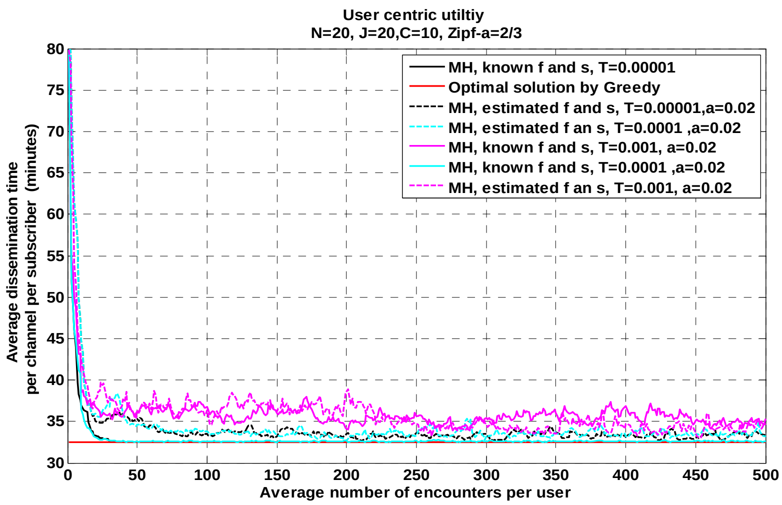
We simulate a random mixing mobility where each user encounters other users uniformly at random. In such a system, we indeed have that the dissemination time for any channel depends only on the portion of the nodes that forward a given channel (Section 3.1).

We consider a small and a large-scale system where for the former the number of users and the number of channels are set to 20 while for the latter the number of users is 200 and the number of channels is 100. For the fractions of subscribers per channel $\vec{s}$, we assume a Zipf distribution with the scale parameter equal to either 2/3 or 1. The former value is motivated by the empirical distribution derived from the Zune data (Fig.5 discussed in Section 5) while the latter value was used in previous work [1]. For the objective of the system welfare, we consider both the channel and user-centric cases with the utility function $V_j(f_j) = -t_j(f_j)$ for channel j, where $t_j(f_j)$ the dissemination is time and f_j is the fraction of forwarding nodes. In particular, we admit Eq.(7). In cases when $\vec{f}$ or $\vec{s}$ are locally estimated, each node uses an exponential weighted averaging with the smoothing constant (weight of a sample) set as follows. For the estimation of $\vec{f}$, the constant is set to 0.02. For the estimation of $\vec{s}$, the constant is equal to 0.02 for the channel and user-centric case, respectively.

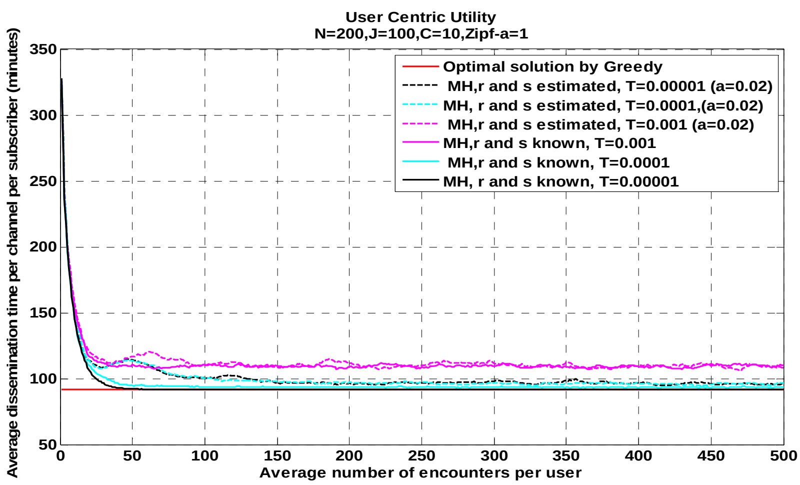
In Fig. 8, we present the results obtained for the channel-centric case. The graphs show the mean dissemination time per channel, i.e. $(\sum_{j \in J} t_j(f_j))/J$, versus the number of encounters per node. We show the results for the Metropolis-Hastings with $\vec{f}$ assumed to be either known or locally estimated by individual nodes. We observe that the system welfare under the Metropolis-Hastings algorithm concentrates near the optimum system welfare. The results in Fig.8 indicate a faster concentration in cases when $\vec{f}$ is globally known. In Fig. 9, we present analogous results for the user-centric case. In this case, we show the mean dissemination per channel i.e. $(\sum_{j\in J} s_j t_j(f_j))/\sum_{j\in J} s_j$, versus the number of encounters per node, with $\vec{f}$ and $\vec{s}$ either globally known or locally estimated by individual nodes. In summary, the presented results in either channel- or user-centric case support the following claim:

> *The system welfare under the Metropolis-Hastings algorithm concentrates nears the optimum system welfare with $\vec{f}$ (and $\vec{s}$ in the user-centric case) either globally known or locally estimated.*

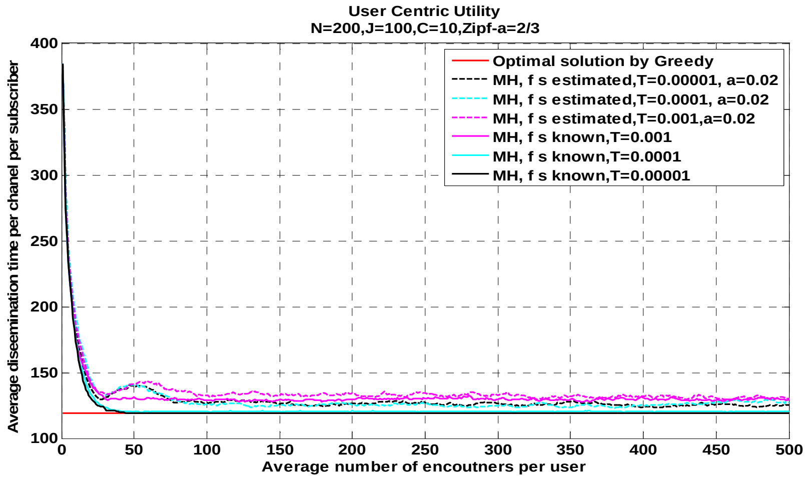
In figure 8(c) (d), the curves are not monotonically decreasing and converged to the optimal solution of Greedy, because Metropolis-Hasting algorithm converges to optimal value step by step in a probabilistic way. There is always probability that the global utility decreases a little at one step of the iterations before it eventually converges to optimal solution. It is also the case that the Metropolis-Hasting are constraint by a local maximum before it converges to the global optimal.



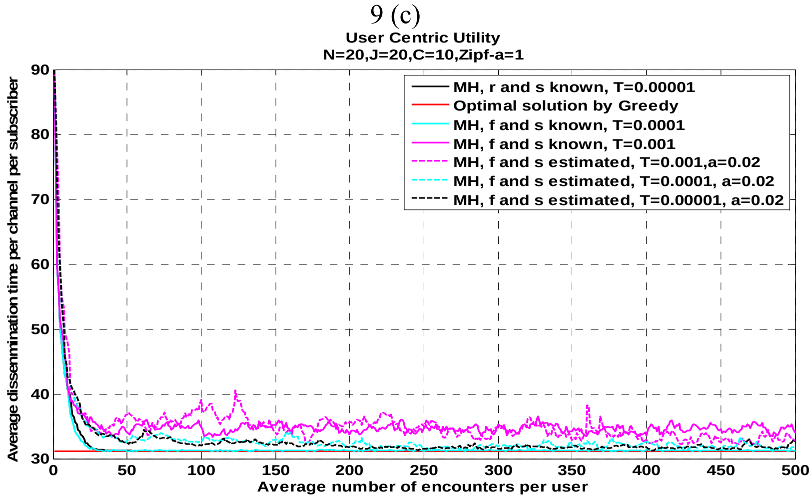
9 (a)



9 (b)



9 (c)



9 (d)

Figure 9: Same as in Fig. 8 but for the user-centric case.

7.2 Real Trace Mobility

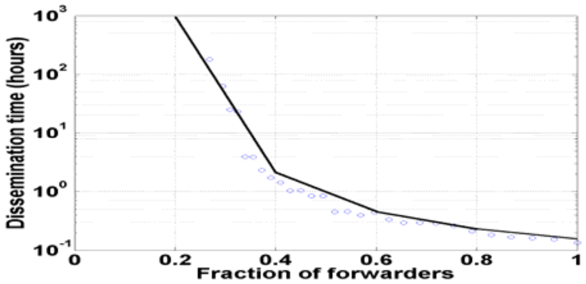
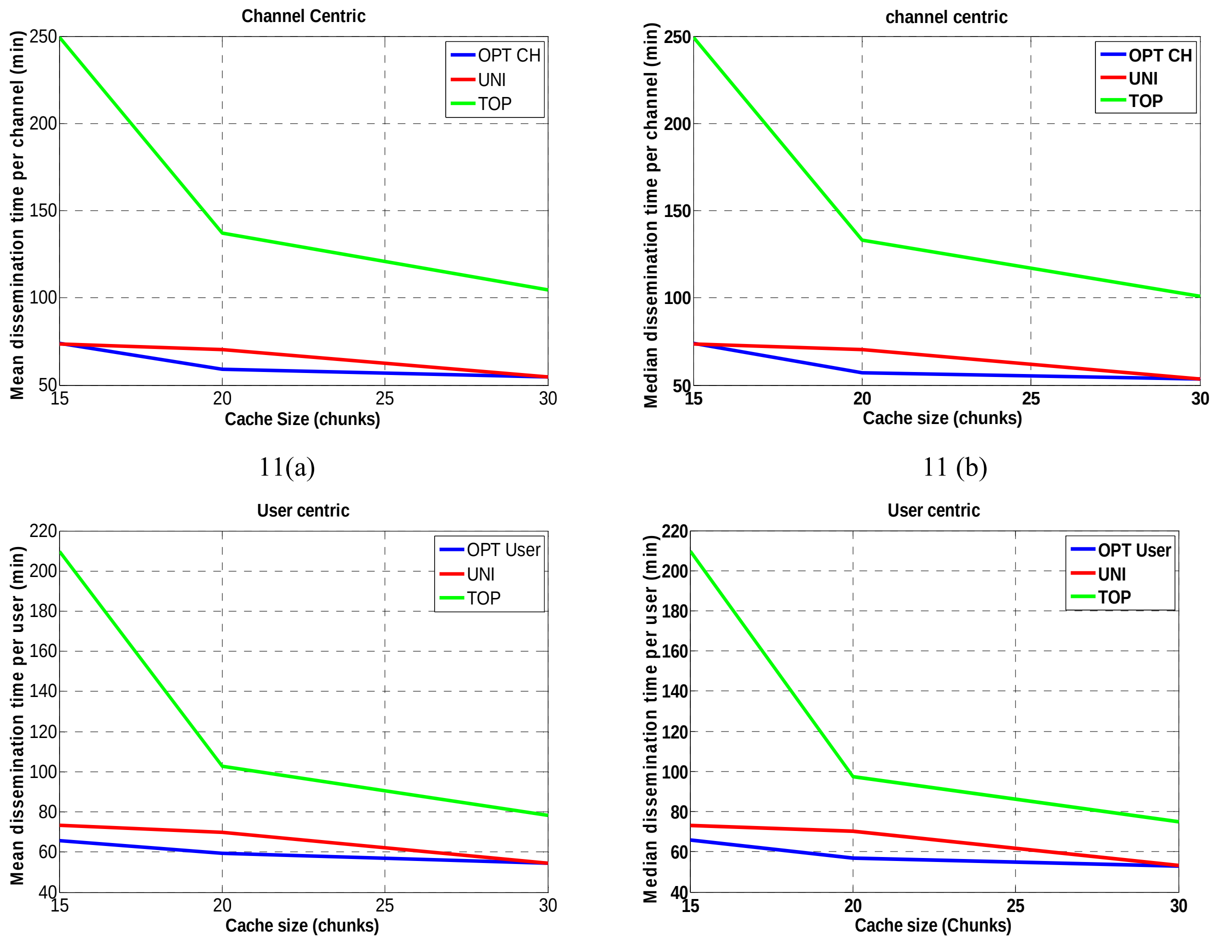


Figure 10: Empirical dissemination curve for the target fraction of nodes α = 0.25 from the CAM mobility trace.

We compare the system performance under the assignment of channels to users that optimizes a system welfare (OPT) with that of heuristics Uniform (UNI) and Top Popular (TOP), respectively introduced in Sec. 4.2.1 and Sec. 4.2.2. Our goal is to demonstrate that OPT can do a better job compared to the heuristics UNI and TOP.

We define the system welfare using the dissemination function $t_j(f_j)$ inferred from the mobility trace CAM and letting $V_j(f_j) = -t_j(f_j)$ as in the preceding section. Specifically, we define the logarithm of $t_j(f_j)$ by a concatenation of linear segments that closely follow the empirical data as showed in Fig.10. While different methods could be used to infer a dissemination curve like that in Fig.10, we relied on hand-picking which suffices for our purpose. We first consider a scenario with J=40 channels, 10 subscriptions per each user. We assume the channel subscription rates follow a Zipf distribution with the scale parameter equal to 2/3. The dissemination time alpha is set to 0.5. For each setting of the simulation parameters, we repeat the experiment five times, each time injecting a message of a channel to a user picked uniformly at random from the users who are either subscribers or helpers for given channel at the beginning of the trace. Recall that there are 36 distinct users in the CAM data and note that the encounter rate η = 0.001 per second, i.e. 1.2 users every two minutes.



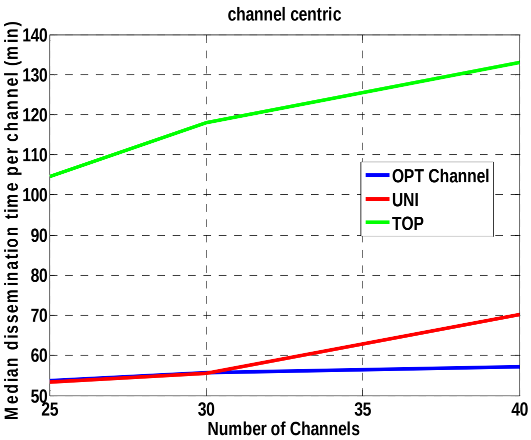
11(a) 11 (b)

11 (c) 11 (d)

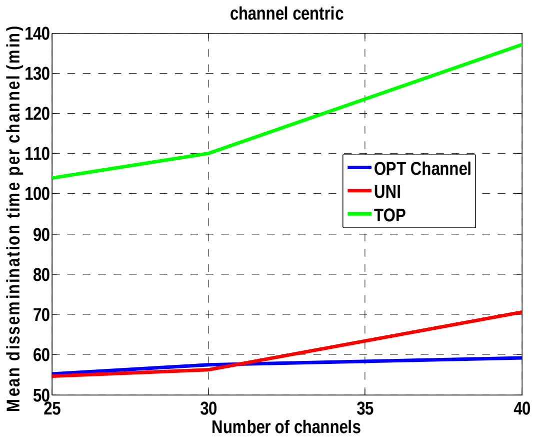
Figure 11: Optimum system welfare VS heuristics under the variable cache size per node

Fig.11 shows the median and mean dissemination time per channel, and per user, for the channel and user-centric cases respectively, under the impact of various public cache size. In the x-axis, the unit is number of channels or chunks. In the y-axis, the unit is minutes. Fig.11 (a) (b) shows the median and mean dissemination time per channel for the channel-centric case, under the public cache is 15, 20 and 30 channels. In terms of dissemination time per channel, it is observed that OPT always achieve the best performance among OPT, UNI and TOP under all public cache size. OPT can far outperform TOP under all public cache size. Also, OPT outperforms UNI when public cache is 20 channels. When the cache size is 15 and 30 channels, OPT has the same performance as UNI. Fig.11 (c) (d) shows the median and means dissemination time per channel per user for the user-centric case. We observe the same trend as fig.11 (a) (b), where OPT always performs best under various public cache size while UNI can perform as good as OPT in some scenarios.

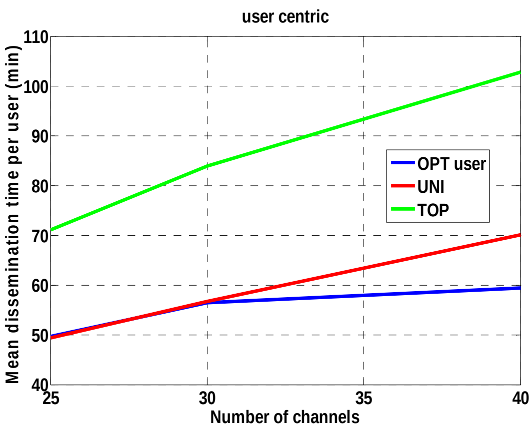
We secondly consider a scenario with 10 subscriptions per each user, and 10 channels to help per each user. We assume the channel subscription rates follow a Zipf distribution with the scale parameter equal to 2/3. The dissemination time alpha is set to 0.5. We change the number of channels from 25 to 40 and compare OPT, UNI and TOP



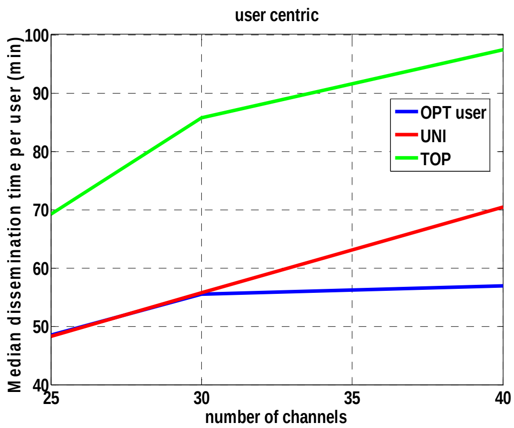
12 (a)



12 (b)



12 (c)



12 (d)

Figure 12: Optimum system welfare VS heuristics under the variable number of channels

Fig 12 (a) (b) shows the mean and median dissemination time per channel for the channel-centric case, under the number of channels is 25, 30 and 40. In the x-axis, the unit is number of channels or chunks[9]. In the y-axis, the unit is minutes. In terms of dissemination time per channel, it is observed that OPT always achieve the best

[9] We assume one chunk per channel. Thus chunk or channel is the same unit.

performance among OPT, UNI and TOP under all sets of number of channels. OPT can far outperform TOP under all number of channels. Also, OPT performs as good as UNI when the number of channel is 25 and become far better than UNI as the number of channel increases up to 40. Fig.12 (c) (d) shows the median and means dissemination time per channel per user for the user-centric case. We observe the same trend as fig.12 (a) (b), where OPT always performs best under various number of channels while OPT brings more performance gain when the number of channels becomes large.

TABLE I
PER-CHANNEL AND PER-USER DISSEMINATION TIMES IN MINUTES FOR CAM TRACE.

Channel-centric	UNI	TOP	OPT
Median	70.2500	133.1000	52.1429
Mean	70.4700	137.1250	57.2000
User-centric	UNI	TOP	OPT
Median	70.4028	97.4528	56.9333
Mean	70.0578	102.7284	59.4089

In Table 1 we present the median and mean dissemination time per channel, and per user, for the channel- and user-centric cases, respectively. We consider a scenario with J=40 channels, 10 subscriptions per each user, and 10 channels helped by each user. We assume that the channel subscription rates follow a Zipf distribution with the scale parameter equal to 2/3. For both mean and median dissemination time, OPT substantially outperforms UNI and TOP for either channel-centric or user-centric case. In particular, in the channel-centric case, OPT achieves over 70 minutes less dissemination time than TOP and over 10 minutes less dissemination time than UNI for both mean and median dissemination time. In the user-centric case, OPT achieves over 40 minutes less dissemination time than TOP and over 10 minutes less dissemination time than UNI for both mean and median dissemination time.

Furthermore, in Fig.13, we show the mean dissemination time for each channel. We note the following. First, under the channel assignment UNI, some intermediate popular channels may be penalized with a high dissemination time. In particular, in Fig.13, we note that the tenth most popular channel gets as much as five hours larger dissemination time than under other channel assignments. Second, same can happen under TOP where the results conform to the expected bias against less popular channels. To be specific, many less popular channels get as much as several hours larger dissemination time than under other channel assignment. The results demonstrate cases where assigning channels by optimizing a system welfare avoids penalizing some channels which can occur under the heuristics such as UNI or TOP.

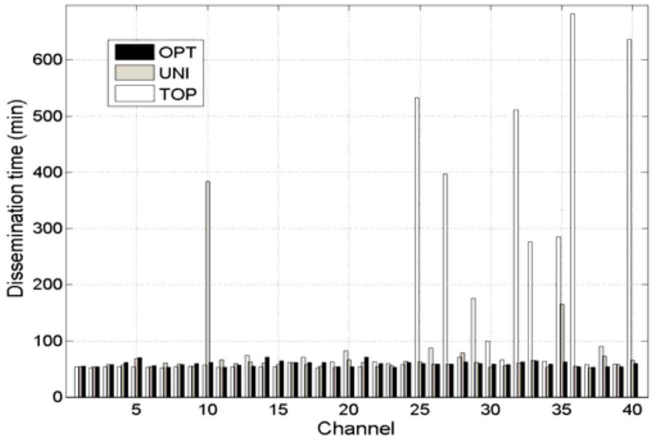


Figure 13: Mean channel dissemination time under CAM mobility with channel centric system welfare. Channels are enumerated in decreasing popularity (i.e. channel 1 is most popular one).

8. RELATED WORK

[1] proposes several heuristics for content exchange between devices based on the inferred preference of the user owning a device and that of encountered devices. Each device is assumed to forward an unlimited number of feeds and prioritizes the download of pieces of the content feeds from encountered devices. Feeds subscribed by a device are prioritized over other feeds. In addition, each device uses a solicitation strategy to decide which pieces to fetch from encountered devices. Specifically, the solicitation strategies considered in [1] include the most solicited and uniform which essentially correspond to the top popular and uniform channel assignments considered in the present paper. The approach in [1] was to evaluate the system performance for a set of solicitation strategies. In this paper, our approach is different–we start with a system welfare objective from which then a channel prioritization strategy follows.

Another related system is CarTorrent [2] proposing a peer-to-peer file sharing tailored for vehicular network scenarios by using epidemic-style content dissemination. Our work is distinct from that on epidemic-style dissemination in that unlike to previous work our focus is on efficient dissemination of multiple content streams.

A related line of research is that of peer-to-peer storage. [15] modelled a peer-to-peer data sharing system, originally proposed in [16], where the goal is to enable access to the content in cases when the access to the Internet is limited. The focus of the work was on the performance of various cache policies under constraints on the cache size at individual devices. Several content replication strategies were investigated in [17]. In these systems, nodes query for the content through multiple hops which is supported by the system. Our work has some similarity with that of peer-to-peer storage in that our system welfare amounts to deciding what portion of nodes should ”cache” a given channel. Note, however, that our objective is different–our goal is to optimize caching of channels with respect to the channel dissemination times that derive from the underlying mobility of devices.

Another system welfare problem was recently considered in [18] but for a different problem. The authors were concerned with optimizing the access rates of mobile devices to a server.

Last but not least, we mention the work on characterization of real-world mobility. An early analysis of human mobility was presented in [19] where it was found that the distribution of the inter-contact time between mobile de- vices decays as a power-law over a time period ranging from minutes to portion of a day. In [7], it was found that this distribution, in fact, is well characterized by power-law decay with an exponential cut-off. The authors in [20] studied the diameter of random temporal networks. On the basis of analytical and empirical results, they found that such networks are characterized by a small diameter. Furthermore, the age of single epidemics was recently characterized in [21].

9. CONCLUSION

We proposed a framework for optimizing the dissemination of multiple information channels in wireless ad-hoc networks. The problem amounts to finding an assignment of users to channels for forwarding the content of channels that optimizes given system welfare. We showed that system optimum assignment can be found by a centralized greedy algorithm. Moreover, we proposed a distributed algorithm using the Metropolis-Hasting sampling that stabilizes around the system optimum. We also discussed how to incorporate the battery expenditure of devices into the optimization framework.

The work opens several interesting directions for future investigation. First, it is of interest to examine the relation between the dissemination time and the fraction of the forwarding nodes across a large set mobility traces. Second, our distributed algorithm involves control over two timescales, slow timescale for the assignment of the users to channels and fast timescale for the online estimation of the parameters – it is of interest to examine the rates of convergence of the two controls. Third, it may be worth considering other Metropolis-Hastings rewiring for speeding up the convergence and alternative online estimators for fast and robust estimation. Forth, it would be important to examine which particular system welfare objectives would be of particular interest in practice. Fifth, one may analyze the gap between the problems SYSTEM and SYSTEM-R. Sixth and last, it is of interest to consider the system welfare problem proposed in this paper in scenarios where the dissemination time of a channel depends not only on the number of the nodes that forward the channel but also on which nodes in particular are the forwarding nodes.

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Paper C

Reputation system for user-generated podcasting under community based mobility model

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Reputation system for user-generated podcasting under community based mobility model

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ABSTRACT

With the popularity of user-generated content and stream media service, the traditional wireless content distribution over infrastructure wireless network becomes not cost-effective and scalable for user generated content sharing and bulk data deliveries, due to inherently limited radio spectrum. We propose a wireless P2P content distribution over intermediate connected opportunistic people network. The content is disseminated from the source to many destinations via short-range wireless data exchange and node local storages while nodes are on the move and meeting. We focus on designing local forwarding and cache management schemes. In such a distributed and dynamic network environment, designing efficient content forwarding and cache management schemes are challenging due to the lack of global podcast channel popularity information at each individual node. We design a distributed reputation system at each node for estimating the global channel popularity information, as a significant part for forwarding and cache management decision. We are interested in the performance of reputation system under Community-based Random Way-Point (C-RWP) mobility model and localized channel popularity distribution. The performance evaluation under three C-RWP scenarios shows that, compare to History-based rank scheme, the reputation system brings more performance gain when channel popularity distribution becomes more localized and node mobility become more localized.

Categories and Subject Descriptors

C.2.4 [Computer System Organization]: Computer Communication Networks-Distributed Systems; I.6 [Computing Methodologies]: Simulation and Modelling

General Terms

Algorithms, Performance, Design

Keywords: Reputation system, ad-hoc podcasting, User Generated Service, Bayesian Framework

1. Introduction

With the popularity of user-generated content (UGC) services, we envision a novel wireless content distribution architecture where content is disseminated from source to the potential receivers by peer-to-peer content sharing in intermediate node and node mobility. We call it wireless peer-to-peer content distribution over people opportunistic network. By exploiting short-range wireless connectivity of handhelds carried by people, this architecture is envisioned to provide more nature and scalable way of sharing user-generated content in a time-variant intermediate connected wireless ad-hoc network. Indeed, limited by its network capacity, the traditional content distribution by the cellular network becomes not scalable when the streaming media service becomes popular. This becomes even worse in the case of UGC services where uploading and publishing content from single user are popular. In this case, the uplink of cellular network can become saturated, because uplink usually has much lower bandwidth than the downlink, which is optimized for client-server content distribution model. Peer-to-peer content distribution exploring the local wireless connectivity and node mobility aim at providing much larger service capacity per source-destination pair as the number of nodes increases [7]. The larger capacity is achieved at the expense of longer delay. There already exist many applications can tolerant longer delay such as e-mail and large scale software updates etc.

In contrast to peer-to-peer content distribution over Internet, the content is locally stored within the network consist of handheld devices carried by people and moved around to potential interested receivers by people mobility. Typically, each node stores not only its interested data but also a limited amount of data for public interests; Every time when two nodes meet, they exchange both their private interested data and public interested data according to the local policy of data forwarding and cache management at each node.

We focus on the design of efficient distributed algorithm for data forwarding and public cache management under multiple content channels. The challenges are time-variant node mobility, the long inter-contact time of node pairs, short contact time of node pairs, and limited cache that user contributed for storing public interested content. Under such a resource constraint environment, which channel the node should store and forward for public good is a question. Any heuristic or optimization framework of forwarding and public cache management needs to explore the context information of data channels or the social network connectivity of mobile nodes. Examples of channel context information are channel popularity, channel scarcity, channel rating etc. Thus the efficient distributed context learning algorithm is desired before any heuristics or optimization framework can be designed.

In this paper, we design a distributed reputation system based on Bayesian framework through which each node can locally estimate the global channels popularities. The popularity of channel is represented by the reputation rating. The reputation system consist of three parts: Firstly, the reputation rating of channels at each node is built and updated by the number of requests to each channel from encounter nodes. This is called the first hand information of channel popularity as they are each node's direct observations. Secondly, reputation rating is also updated by integrating its encounter nodes' direct observations which is called the second hand information of channel popularities. By dong so, node can learn and adjust popularity information of channels from observations made by others even before having to learn by own experience. By gossiping the channel reputations among meeting nodes, the accurate channel popularity information can propagate much faster throughout the network, especially when the popularity distribution is localized. Moreover, to protect against rumor spread from liars, the second hand information is only accepted if a deviation test is passed. Thirdly, to adapt the channel popularity shifts, both the first hand information and the reputation ratings of each channel decays after each node contact. The previous observations are gradually forgotten while more weight is put on recently observations.

To the best of our knowledge, our work is the first work on employing Bayesian framework based reputation system for context-aware opportunistic data dissemination. The focus of this paper is to study the performance of reputation system under community-based mobility model and localized channel popularity distribution. Previous, the Bayesian framework based reputation system has been studied in the context of homogenous mobility model and homogenous channel popularity distribution [3]. The paper is organized as follows: in section 2, the protocol specification and data structure of reputation system are described. In section 3, the concept of Bayesian framework based reputation is introduced. We present the community-based random way point mobility model and localized channel popularity distribution in section 4. We evaluate the performance of reputation system by discrete event simulation in section 5. Section 6 concludes the paper.

2. Data Structure and Protocol Specification

The cache at each node consists of a private cache (for storing node's private or own interested channels) and a public cache (for storing public or other nodes' interested channels). Each node maintains a table of channel reputation ratings which is used for content forwarding and public cache replacement decisions. As an example, the reputation rating table of node A is shown in table 1.

Table 1: Reputation Rating Table

Reputation Rating Table at node i

Channel Feeds	First Hand Information	ReputationRating	Entries and Metadata	Private or Public
1	$A_{i,1}, B_{i,1}$	$R_{A,1}$	Entry 1 Entry 2	Private
3	$A_{i,3}, B_{i,3}$	$R_{A,3}$	Entry 1 Entry 2	Private
5	$A_{i,5}, B_{i,5}$	$R_{A,5}$	Entry 1 Entry 2	Private
7	$A_{i,7}, B_{i,7}$	$R_{A,7}$	Entry 1 Entry 2	Private
9	$A_{i,9}, B_{i,9}$	$R_{A,9}$	Entry 1 Entry 2	Public
......	....	....	....	......
j	$A_{i,j}, B_{i,j}$	$R_{i,j}$	....	Public
.....	....	....	....	......

Channel Feed: information Channel identifier

$A_{i,j}, B_{i,j}$: first hand information of channel j at node i.

$R_{i,j}$: reputation rating of channel j

Entries and Metadata: A list of entries and their metadata for the information channel

Private or Public: indicator of the information channel that is either subscribed or helped by the node.

When two nodes meet, there are two phases on exchanging content. They firstly exchange the updates of their subscribed channels. Secondly, if they remain connected, they start exchange updates of their helped channels in public cache based on a pre-defined local channel forwarding and cache replacement scheme. The public content exchange are based on “pull” operation from receivers, i.e. node proactively ask peer node for the data they are willing to carry for public good based on its local policy. This avoids data flooding throughout the network thus improve service scalability. During public content exchange phase, there are two sub-phases: (a) nodes update the channels that they currently help disseminating; (b) nodes replace the channels that they help disseminating with new channels (from peer node) based on public cache replacement policy. In this work, we assume (a) is done before (b) under the assumption that only limited data can be exchanged in a node contact. We also evaluate the impact when (b) is done before (a) and it turns out the difference is minor, thus we does not show that results here.

In brief, the protocol specification of reputation system based podcasting is as follows: (As two nodes behave in a symmetric way, we only describe behaviours of one node for simplicity reasons.)

1. Idle node periodically broadcast association requests to its neighbours. If it discovers several neighbouring nodes, it randomly selects one node to associate and establish a pair-wise connection.
2. Node updates its estimated popularity of all channels by merging the second hand information from peer based on Bayesian reputation system [Event 1].
3. Node firstly pulls updates of private interested channels from peer node [Event 2].
4. Upon peer node request updates of its privately interested channels [Event 3], node updates first hand observation of its estimated channel popularity based on Bayesian reputation system.
5. Node pull content of public interested channels based on its estimated channel popularities and forwarding && cache replacement schemes [Event 4]. Various forwarding and public cache replacement schemes are described below.
6. Content synchronization complete or two nodes move away from the radio coverage.

For the detailed descriptions of protocol specification, see the message sequence chart of figure 1 (suppose node A and node B establish a pair-wise association).

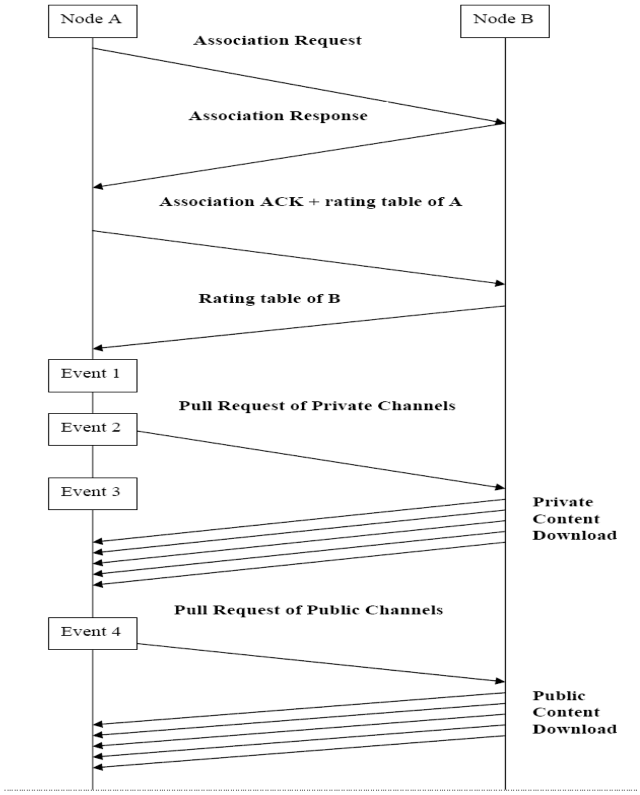

Figure 1: Message Sequence Chart

Public-interested channel forwarding scheme:

Most (M): Based on node's local channel popularity estimation, node firstly forward the content of the most popular public-interested channel from its peer node if there is new update, then the second most popular one, the third most popular one and so on, until the association of two nodes breaks either when they move apart from each other or the data exchange of two nodes complete. The aim of forwarding most popular channel first is to maximize the probability that future encounters would be interested in requesting it.

Probabilistic (P): node decides to forward a public-interested channel with a probability proportional to its popularity (by the node's local estimation). This scheme gives most network capacity to most popularity channels while still gives certain network capacity to intermediate and low popular ones.

Uniform (U): A node decides which channels to forward content with equal probability. The network capacity is evenly given to all the channels exclude the channels that one subscribes. Thus, node does not need to estimate the popularity information of channels for forwarding decisions.

Public cache replacement scheme (public-interested channel replacement scheme): When the public cache of a node is full and there are new public-interested channels at peer node, one has to decide whether to replace channels already in the public cache with new public-interested ones from peer. If it decides so, it also needs to decide which public-interested channels to replace. Suppose node u meets node v where F(u) is list of forwarded channels at node u and F(v) for node v. S(u) and S(v) are the set of subscribed channels for node u and v. During channel replacement, typically node u selects its list of helped channels from the set F(u) U F(v) \ S(u). And node v selects its list of helped channels from the set F(v) U F(u) \ S(v).

Most (M): Only if the new channel from peer is more popular than the least popular public-interested channel in the public cache, node can replace with this new channel. If so, the least popular channel in public cache will be replaced by this new public-interested channel from peer. The channel popularity is based on the node local popularity estimation. In other words, node select the list of helped channels from F(u) U F(v) \ S(u) according to the decreasing channel popularity.

Probabilistic (P): When public cache is full, node select the list of helped channels from F(u) U F(v) \ S(u) with a probability which is proportional to its popularity (based on node local rating table).

Uniform (U): When public cache is full, node select the list of helped channels from F(u) U F(v) \ S(u) with equal probability. Nodes do not need to have the channel popularity information.

3 Bayesian Framework Based Reputation System

3.1 Standard Bayesian Framework

Node i model the popularity of channel j as an actor in the base system as follows. Node i thinks that there is a parameter θ such that the channel i is interested by any node with probability θ. The outcome is drawn independently from observation to observation (node i thinks there is a different θ for different channel j while different node i may have different believe in different parameter θ). The parameters θ are unknown, and node i model this uncertainty by assuming θ itself is drawn according to a distribution (the "prior") that is updated as new observations become available. We use Beta (A, B) as the prior distribution since it is suitable for Bernoulli distribution and the conjugate is also a Beta distribution. The standard Bayesian procedure is as follows. Initially, the prior is Beta (1, 1), the uniform distribution [0, 1]; this represents absence of information about which θ will be drawn. Then after (f+s) observations during contacts with encounter nodes, say with s times the channel i is requested by encounter nodes while f times it is no requested by encounter nodes. The prior is updated:

$$A := A + s\,,\ B := B + f\ .$$

If θ, the true unknown value is constant, then after a large number m of contacts:

$$A \approx n\theta\,,\ B \approx n(1-\theta)$$

And Beta (A, B) becomes closes to a Dirac at θ, as expected. We denote E (Beta (A, B)) as the expectation of Beta (A, B). Thus we can estimate θ as follows:

$$\theta \approx E(Beta(A, B)) = \frac{A}{A+B}$$

3.2 First hand information by modified Bayesian approach

The first hand information for the popularity of channel j at node i is defined as:

$$\mathrm{F}_{i,j} = (A_{i,j}, B_{i,j})$$

This represents the parameters of the Beta distribution assumed by node i in its Bayesian view of the popularity of channel j as an actor in the base system. Initially, it is set to (1, 1). The standard Bayesian method gives the same weight to each observation regardless of its time of occurrence. However, the popularity of a podcast channel may change when nodes move between different communities with different channel popularity distribution. For this reason, we add a reputation fading mechanism to give less weight to the past observations, because the latest observations would be more important for estimating current and future popularity of the channel. Assume node i makes one individual observation of channel j during a contact with encounter node. Let s=1 if channel j is requested by the encounter node, and s=0 otherwise. The update is as follows:

$$A_{i,j} := u \bullet A_{i,j} + s\,, \qquad B_{i,j} := u \bullet B_{i,j} + (1 - s)$$

The weight u is a discount factor for the past experiences, which serves as the fading mechanism.

3.3 Reputation Rating and Model Merge

The reputation rating of channel j at node i is defined as $R_{i,j}$:

Initially $R_{i,j} = E(Beta(A_{i,j}, B_{i,j})) = \dfrac{A_{i,j}}{A_{i,j} + A_{i,j}}$, $(A_{i,j}, B_{i,j})$ is set to (1, 1).

It is built and updated on two types of events: (1) when first-hand information is updated by own observations; (2) the second hand information from encounter nodes are accepted and copied. There are two variant of using second hand information from encounter nodes: direct observations (first hand information) from encounter nodes and reputation rating from encounter nodes. For event type (1), the update of reputation rating is the same for the first-hand information updating. Let s $\in$ {0, 1} is the observations:

$$A_{i,j} := u \bullet A_{i,j} + s, \quad B_{i,j} := u \bullet B_{i,j} + (1 - s)$$

$$R_{i,j} = E(Beta(A_{i,j}, B_{i,j})) = \frac{A_{i,j}}{A_{i,j} + B_{i,j}}$$

For the case (2), if we assume passing direct observations, the linear pool model is used to merge own reputation rating with direct observations passed from encounter nodes on the condition if the deviation test is passed. Deviation test is used to protect system against false rating from encounter nodes. The idea behind it is that humans only believe the opinions from others only if, to them, it seems likely i.e. it dose not differ too much from their own opinions. Moreover, even if they accepted opinions from others, they only attach less weight to other's opinions than their own opinions. Let

the first hand information of channel j at encounter node x:

$$\mathrm{F}_{x,j} = (A_{x,j}, B_{x,j})$$

The deviation test is as follows:

$$\text{If } \left| E(Beta(A_{i,j}, B_{i,j}) - E(Beta(A_{x,j}, B_{x,j})) \right| < \text{THS}$$

(THS is a positive constant (deviation threshold)), then the deviation test is passed and we believe the report from node x is trustworthy. Then, α_i^j, β_i^j are updated by first hand observations of node x using the linear opinion pool model merging:

$$R_{i,j} = (1-w) \bullet R_{i,j} + w \bullet \frac{A_{x,j}}{A_{x,j} + B_{x,j}} \quad 0<w<1.$$

4. Community-Based Random Way-Point model and Localized Channel Popularity Distribution

Community-based Random Way point (C-RWP) captures the "clustering" effect of realistic human mobility: The mobility of nodes tends to be localized in certain geographical area where they frequently meet nodes of the same community with similar social roles e.g. workmate, classmate; On the other hand, nodes only occasionally meet nodes with dissimilar social roles in other geographical areas. In C-RWP, nodes are divided into different communities. One community is a group of nodes with the similar mobility patterns. For the simplicity of analysis, nodes of one community move within a square following a random way-point (RWP) mobility model. Nodes that move in the same square have equal chance of meeting each other frequently, while nodes that move in different squares can seldom meet each other, except that they only occasionally meet near the border of two squares.

Secondly, we assume the popularity distribution of data channel is heterogeneous over various communities of nodes. This is indeed confirmed by empirical studies. For instance, based on the measurement results of YouTube, a recent paper [5] shows that: video clips of local interests only have a high local popularity; there is no correlation observed between global and local popularity. Along the line of their observations, we assume: firstly, one community of nodes have one group of interesting channels which is a subset of total global available channels. Within one community of nodes, the popularity of the group of subset channels follows Zipf-like distribution. Secondly, different communities have different groups of interested subset channels. One example could be one community is interested in the channels of English language while other is interested in channels of German language.

Thirdly, we make assumptions of the location of channel publishing nodes and channel subscribing nodes. The location of the channel publishing nodes and its subscribing nodes could be as follows: (1) the publishing node and its subscribing are in the same community i.e. they moves within the same geographical area; (2) they are in two different communities (geographical areas) which are partially or totally physically separated; (3) publishing node and some of its subscribing node are in the same community (geographical area) while other subscribing nodes are in other community (geographical area). We focus on the scenario (2): due to physical separation of communities (geographical area), nodes of one community may have difficulty of learning popularities of channels published from other communities (geographical area).

5. Performance Evaluation

In this section, by discrete event simulation, we evaluate the performance of reputation system under "Community-based Random Way-Point" (C-RWP) mobility model and localized channel popularity distribution.

5.1 Simulation Model

The simulator is based on a simple communication model: two nodes can communicate with a nominal bit-rate if their geometric distance is smaller than a threshold value. We do not model any MAC layer issues such as collision or interference, since we assume networks are sparsely connected where collisions and interference between different associations are rare. Nodes only associated pair-wise, even if more than two are within reach of one another. The reason is that the contact duration may be short and it is better to get high throughput by only sharing the transmission capacity between two parties than to get high connectivity. We assume the forwarding scheme is "Most" and public cache replacement scheme is also "Most". This combination gives the best performance under the ideal knowledge of channel popularity at each node [3]. The channel popularity at each node is locally represented by reputation ratings. As described in section 2, with "Most" forwarding scheme, node forward the content from the most popular channels to least popular channels until two nodes get disconnected because of their mobility or when both nodes complete data exchange. By “Most” public cache replacement scheme, when public cache is full, the content of less popular channel is always replaced with content of more popular one. Other simulation parameters are summarized in table 2.

Table 2

Parameters of Reputation System	
THS	0.4
u	0.99
w	0.2
Other Parameters	
Cache size	2 GB
Public Cache size	60 MB
Chunk size	2 MB
Simulated time	12 hours

5.2 Performance Metrics

To quantify user satisfaction of user generated podcasting, Recall is employed as the performance metrics of reputation system. Recall is defined as the fraction of node’s own subscribed chunks that are successfully received before a time deadline T by time t. It is borrowed from the area of Information Retrieve (IR). By having a time deadline T, Recall inherently incorporate the effect of data delivery delay (define as the latency between the time when chunk is published and the time when it is received). For obsolete ad-hoc podcast service, both delivery ratio and delivery delay are important for the end user satisfaction. Recall of node i by time t is defined as:

$$R^{i}(t) = \frac{X_{R}^{i}(t)}{X_{p}^{i}(t)}, i = 0,1,2 \dots N - 1$$

N: the total number of nodes; i: the node ID.

$X^{i}_{R}(t)$: the total number of private subscribed chunks that have been received by node i before deadline T by time t.

$X^{i}_{P}(t)$: the total number of private subscribed chunks that have been published from all node i's interested channels by time t.

Average recall is defined as the average recall over the total number of nodes N. In this work, we are only interested in the average recall at the end of the simulation t = simulation time 12 hours. Also the deadline T is set to the simulation time 12 hours. Since we target at delay-tolerant services such as large scale software updates or news bulletin, user typically tends to retrieve the content regularly with large time interval such as one or two days. Thus, the deadline 12 hours is a good indicator for end user satisfaction.

5.3 Simulation Results

We compare the performance of reputation system with history-based rank [1] under three scenarios: 1. two separated communities of nodes and two groups of localized popular channels. 2. four separated communities and two groups of localized popular channels. 3. four separated communities and four groups of localized popular channels. The history-based rank method [1] is a method which estimate channel popularity only by first hand information (in the form of number of encounter requests per channel). It works as follows: node keeps track of the channels that were requested by past encounter nodes and maintains a history-based ranking. Only the requests for channels that encounter nodes subscribed are counted, i.e. channels that encounter nodes helps dissemination are not counted. The initial condition of history-based rank is set to "1" for all the channels.

Scenario 1: two separated communities of nodes, two groups of localized popular channels

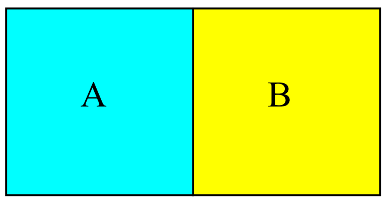

Figure 2: Scenario 1

As indicated in figure 2, 100 nodes are grouped into two communities: A (blue) and B (yellow). The nodes are human beings who carry WiFi-enabled mobile device. Each community is interested in one group of popular channels among total 100 channels. Nodes of ID 0-49 belong to community A while nodes of ID 50-99 belong to community B. Both nodes of community A and B move within a square of the same side length 500 meters in Random Way-Point (RWP) model. The moving speed is constant 1 m/s with pause time 1 s. Each node publishes one channel, with the channel ID identical to the node ID, e.g. node 0 publish channel 0, node 1 publish channel 1. Community A publish channels from 0-49 while community B publish channel from 50-99. The content publish interval per channel is 600 s which is identical for all channels. Community A is only interested in the channels published from community B (channel ID 50-99) while community B is only interested in the channel published from community A (channel ID 0-49). Each node is interested two channels which it subscribes. Among community B, the popularity distribution of channels 0-49 follows Zipf-like distribution with a=1.5, where the channel 0 is the highest popular channel, channel 1 is the second popular and so on. Define the popularity of channel 0-49 in community B:

$$p_i \sim \frac{1}{(i+1)^a}, \text{ i = 0, 1, 2....49}$$

Likewise, among community A, the popularity distribution of channels 50-99 follows the same Zipf-like distribution with a=1.5. Assume the channel 50 is the highest popular channel, channel 51 is the second popular and so on: Define the popularity of channel 50-99 in community A:

$$q_j \sim \frac{1}{(j-49)^a}, \text{ j = 50, 51, 52....99.}$$

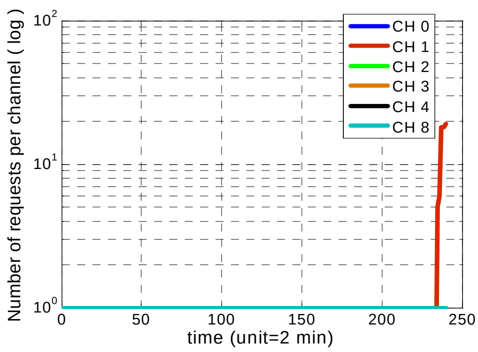

Figure 3: History-based Rank: Number of requests per channel at node 60

In figure 3 and 4, we compare the performance of reputation system and history-based rank in terms of estimation of channel popularity. Without loss of generality, we take the estimation of channel popularity at node 60 for example. The popularity information for a subset of all the channel are shown, in particular channel 0, 1, 2, 3, 4 and 8, to represent both high and intermediate popular channels. From the figures 3 and 4, it is obvious that the history-based rank poorly estimates the popularity of channel 0,1,2,3,4,8. With history-based rank, node 60 cannot get any popularity information of channel 0,1,2,3,4,8 until 460 minutes. The reason is that node 60 cannot have enough first-hand information about channel popularity. In contrast, reputation system can always perfectly estimate the popularity of channel 0, 1, 2,3,4,8 since the very beginning of the simulation as showed in figure 4.

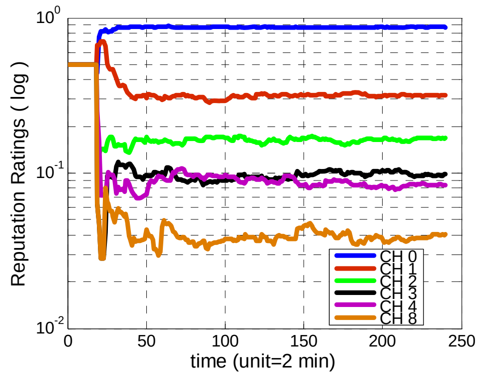

Figure 4: reputation ratings per channel at node 60

Table 3

	History-based Rank	Reputation System
Average Recall	0.015	0.250

The initial condition of history-based rank is set to “1” for all the channels.

Without the enough popularity information, nodes will not be able to forward the channels of data which are interested by its future encounter nodes. Thus the average recall of history-based rank is much lower than reputation system, as showed in the table 3. History-based rank only achieves average recall 0.015, while reputation system achieves 0.250. The performance gain of reputation system over history based rank is more than 20 times.

Scenario 2: four communities, two groups of localized popular channels

As indicated in figure 5, nodes are moving within four identical square areas (communities) (A1, A2, B1, and B2). Popular channels are grouped into two tastes (the red and the blue). Community A1 and A2 (red colour) are only interested in channels of 50-99 published by community B1 and B2, while community B2 and B1 (blue colour) are only interested in channel published by A1 and A2. Node 0-24 are moving within A1 square; node 25-49 are moving within A2 square; node 50-74 are moving within B1 square; node 75-99 are moving within B2 square. Similar to the previous scenario, each node publishes one channel. The channel ID is identical to the node ID. The channel popularity distribution of channel 0-49 in community B1 and B2 follows Zipf-like distribution with a=1.5 (channel 0-49 are published by community A1 and A2). Assume channel 0 is the highest popular channel; channel 1 is the second popular and so on, i.e. ch0>ch1>ch2>ch3…>ch49. Define the popularity of channel i follows Zipf-like distribution:

$$p_i \sim \frac{1}{(i+1)^a}, \text{ i = 0, 1, 2….49}$$

Likewise, the channel popularity distribution of channel 50-99 in community A1 and A2 follows Zipf-like distribution with a=1.5. Channel 50-99 are published from community B1 and B2. Assume the channel 50 is the highest popular channel, channel 51 is the second popular and so on i.e. ch50>ch51>ch52>ch3…>ch99. Define the popularity of channel j follows Zipf-like distribution:

$$q_j \sim \frac{1}{(j-49)^a}, \text{ j = 50, 51, 52….99.}$$

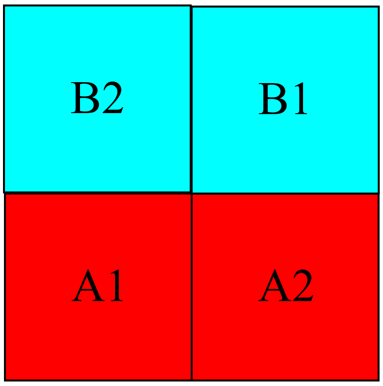

Figure 5: Scenario 2

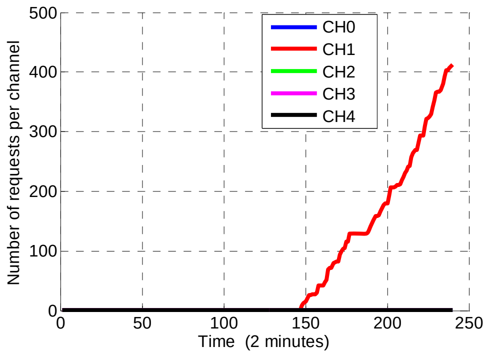

Figure 6: History-based rank: Number of requests per channel at node 60

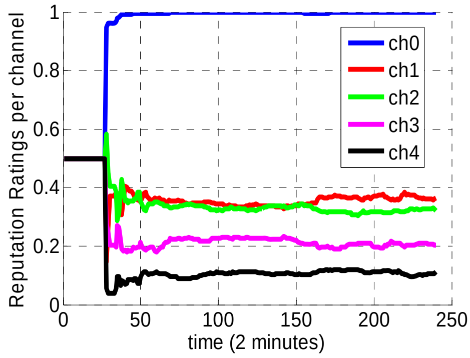

Figure 7: Reputation system: reputation ratings per channel at node 60

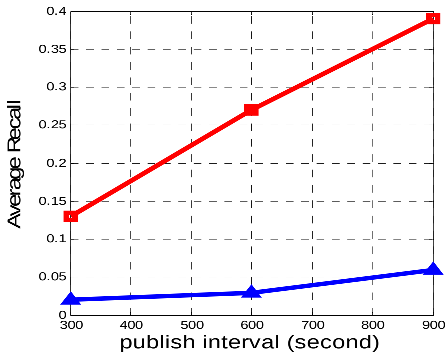

Figure 8: Average Recall

In figure 6 and 7, we compare the performance of reputation system and history-based rank in terms of estimation of channel popularity. Without loss of generality, we take the estimation of channel popularity at node 60 for example. The popularity information for a subset of all the channels is shown, in particular channel 0, 1, 2, 3, 4. From figure 6 and 7, in terms of channel popularity estimation, it is obvious that reputation system far outperforms history-based rank in both in estimation accuracy and estimation speed. In figure 6, before 300 minutes, node 60 has no observations of the channel popularity information of channel 0,1,2,3,4. Even after 300 minutes, except channel 0, 1, node 60 still does not have popularity observations of other channels. In contrast, using reputation system, only after 54 minutes, node 60 can already accurately estimate the popularity ranking of channel 0, 1,2,3,4, as in figure 7.

We compare the performance of reputation system with history-based rank under the impact of publish interval. Simulation Parameters are as follows: Zipf-a=1.5, public cache size=30 chunks, subscribed channel per user = 2, Length of Square=350 meter, Number of Channels=100.

From figure 8, we observe that, as the previous scenario, reputation system far outperforms history-based rank scheme under various channel publish intervals. Secondly, in terms of average recall, the publish interval does not have impact on the performance of history-based rank scheme. When increasing publish interval from 300s to 900s, the average recall increases only slightly from 2.0 % to 6.3%. In contrast, in the case of reputations system, the average recall increases significantly from 0.132 to 0.390 when the publish interval increases from 300s to 900s.

Scenario 3: four communities, four groups of popular channels

As shown in figure 9, nodes are grouped into four communities: A, B, C and D. Nodes of ID 0-24 move within square A area following random way-point mobility model. Nodes of ID 25-49 move within square B area following random way-point mobility model. Nodes of ID 50-74 move within square C area following random way-point mobility model. Nodes of ID 75-99 move within square C area following random way-point mobility model. The four squares A, B, C, D are all identical. Each node publishes one channel (has the same ID as the node ID). The community A is only interested in the channels published by community C i.e. channel 50-74; the community B is only interested in the channels published by community D i.e. channel 75-99; the community C is only interested in the channels published by community A i.e. channel 0-24; the community D is only interested in channels published by community B i.e. channel 25-49. The popularity distribution of channels published from each community follow Zipf-like distribution with a=1.5, e.g. channel 0-24 follows Zipf-like distribution in community C, channel 25-49 follows Zipf-like distribution in community D etc.

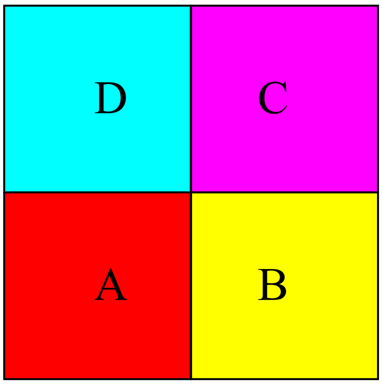

Figure 9: four communities with four groups popular channels

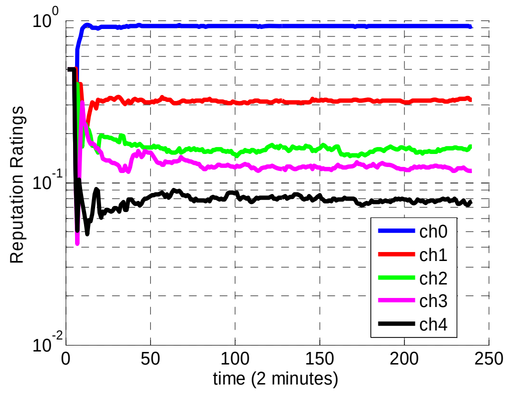

Figure 10: Reputation system: reputation ratings per channel at node 60

In figure 10 and 11, we compare the performance of reputation system and history-based rank in terms of estimation of channel popularity. Without loss of generality, we take the estimation of channel popularity at node 60 for example. The popularity information for a subset of all the channels is shown, in particular channel 0, 1, 2, 3, 4. From figure 10 and 11, we observe that, by using history-based rank, node 60 cannot get any observations for estimating channel popularities. In contrast, with reputation system, the estimation of channel popularity is much more efficient, as reputation system uses both first hand and second hand observations. With reputation system, the popularities of channel 0,1,2,3,4 have been perfectly estimated since the start of the simulation.

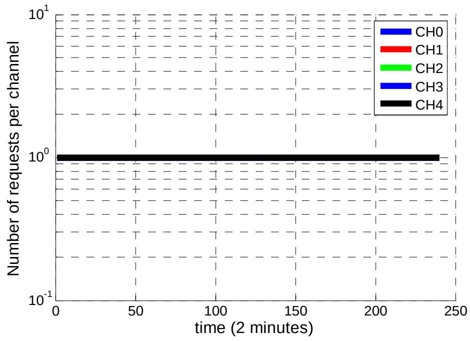

Figure 11: History-based Rank: Number of requests per channel at node 60

As shown in figure 12, with four communities, history-based rank almost always achieves 0 average recall under different publish intervals. With reputation system, the average recall increases from 0.069 to 0.220 when the publish interval changes from 300s to 900s.

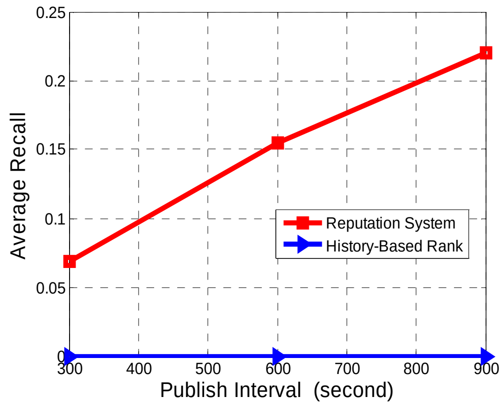

Figure 12: Average Recall

5.4 Summary and Discussion

From scenario 1, 2 and 3, the popularity distribution becomes more and more localized (i.e. from two groups of localized channels to four groups), while the number of channels and number of nodes are the same for all scenarios. In this case, the reputation system gives more performance gain over history-based rank, when the channel popularity is becoming more and more localized. Secondly, from scenario 1 to scenario 2, reputation system does not bring more performance gain over history-based rank, when the node mobility is becoming more and more localized (i.e. from two communities to four communities) while the channel popularity distributions are the same. To summarize, reputation system is more useful in the environment where content channel popularity are very localized and heterogeneous. Secondly, the localized node mobility alone does not have impact on the performance gain of using reputation system.

6. Conclusion and Future Work

We design a Bayesian framework based reputation system for estimating podcast channel popularity in user-generated wireless podcasting. Reputation system enables nodes to share their direct observations of channel popularities. Thus, the accurate channel popularity information can propagate much faster throughout the network, especially when the node mobility is community-based and channel popularity distribution is localized. Our simulation results show reputation system overwhelmingly outperforms history-based rank scheme in terms of average recall under a community-based Random Way Point (RWP) mobility model and localized channel popularity distribution. Besides, the more localized the channel popularity is, the more performance gain can reputation system achieve over history-based rank.

For future work, we plan to study the performance of reputation system under a more realistic mobility model such as [4] which captures node movement both within the communities and between communities.

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Paper D

Heterogeneous Community-based mobility model for human opportunistic network

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ABSTRACT

Human opportunistic networks can facilitate wireless content dissemination while humans are on the move. In such a network, content is disseminated via nodes relaying and nodes mobility (e.g. human mobility). To develop and validate new protocols and services over opportunistic network, it is essential to use real human mobility in the simulation experiment. However, the real mobility traces are limited and their validities are difficult to generalize. We present Heterogeneous Community-based Random Way-Point (HC-RWP) mobility model that can generate synthetic traces that captures important properties of real human mobility: *node heterogeneousness, space heterogeneousness, (short term) time heterogeneousness, (long term) time periodicity*. These properties are based on intuitive observations of daily human mobility and confirmed by the analysis of real mobility traces. By discrete event simulation, we show HC-RWP captures not only the above four observed properties, but also some essential statistic features of real human mobility traces reported in previous studies.

***Index Terms*—human mobility modelling, Delay-tolerant Network, opportunistic networks**

1. Introduction

In recent years, as a new evolution of mobile ad-hoc network, opportunistic network has become an attractive research area for networking small mobile devices carried by human being, vehicles and animals [1]. Opportunistic network is particular useful in challenged environments where the infrastructure network is hard to deploy due to the physical constraints and economic constraints, e.g. disaster-relief, wild-life monitoring and Internet provision for rural areas. As another type of scenario, we focus on wireless content distribution over opportunistic network consist of moving people in urban area. This type of opportunistic network is envision to supplement the traditional cellular networks in terms of extending cellular network coverage and increasing its network capacity, by exploiting node mobility [2]. Within this framework, recently dissemination based routing has attract significant attentions for providing seamless content distribution over opportunistic network such as [3] [4]. However, previous studies assume commonly used mobility model such as Random Way-Point (RWP) in a restricted square. Those models are homogeneous mobility model in the sense that: all mobile nodes behave statistically identical to each other (node homogeneousness); each mobile node uniformly picks up a random trip over a given domain without preference (space homogeneousness); their stationary behaviours do not change over time (time homogeneousness). They do provide scenarios that mathematically traceable, yet they are not able to address the complexity of node mobility in real-life settings. In a realistic setting, we believe the mobility of nodes tends to be heterogeneous in the sense that: each node may have very different mobility pattern; In a short-term time scale (e.g. several hours), each node may visit a number of places very often within a given geographic area than other places outside this area; lastly, node's repeat the same mobility pattern periodically over long term time scale (e.g. every one or several days). In this paper, the notation "node" and "human" are interchangeable.

In principle, real mobility traces could have been more useful in validating new protocols over opportunistic network. However there are several reasons that synthetic model is preferred at this stage. Firstly, public available mobility traces contain limited measurement samples in limited observation period and have very low time granularity. Secondly, each trace is specific to its own scenario and hard to generalize for all cases. Finally, in some cases, mathematical model of human mobility is needed to analytically study the new opportunistic network protocols and services. Math model also allows us to study the sensitivity of various design parameters.

In this paper, we propose a new synthetic mobility model that can well capture the characteristics of real human mobility: Heterogeneous Community-based Random-Way Point (HC-RWP). HC-RWP well captures heterogeneousness of real-life human mobility: *node heterogeneousness, space heterogeneousness and (short term) time heterogeneousness, (long term) time periodicity*. In HC-RWP, nodes tend to move and stay locally at set of frequent visited places for the most of the time, while they occasionally roam to other places. Thus, node often meets other nodes that also move and stay within same set of frequently visited places while by chance meet nodes of other areas. We define, for one mobile node, the set of frequent visited places as "home location" and set of less frequent visited places as "roam location". Nodes of similar localized mobility patterns are defined as a community, i.e. nodes that have identical home location. Various communities have diverse home locations but may have the same roam location. Nodes of the same community often meet and stay together in their home location, while nodes of different communities less frequently meet in their roam location. Various communities can be, for instance, a group of people that work in the same company (say community A), students that study in the same school (say community B). Home location of A is school canteen, lecture hall, student dorm and sport center. Home location of B is Company restaurant, company building, and company sport centre. Community A and Community B can not meet frequently, as they have very different home location. However, they can meet at Shopping Mall and Train station both of which are common places of their roman locations. Finally, the home location of one node may change periodically over time, e.g. In the evening, home location of A may become Student Dorm, Disco pub and Cinema.

The paper is organized as follows: in section 2, we review the related work in real human mobility measurement and modelling. In section 3, we describe the general HC-RWP model and provide a simplified version and its implementation. In section 4, we provide extensive simulation results of HC-RWP model with two purposes: to demonstrate how it captures properties of real human mobility? What are probability distributions of the contact time and inter-contact time of HC-RWP compared with real mobility trace? Finally, we conclude the paper and present future work in section 5.

2. Related Work

The initial inspiration of our work comes from the Restrict Random Way-Point model (R-RWP) presented in [7]. However, their model only captures certain *space heterogeneousness*, but not *node heterogeneousness, (short term) time heterogeneousness, and (long term) time periodicity.*

Inter-contact time and contact time are typical performance metrics for characterizing nodes mobility in mobile opportunistic network. Inter-contact time is the time interval between successive contacts of a specific node pair. Contact time is the time interval that a specific two nodes stay connected before they move apart from the radio range. Inter-contact time corresponds to how often two nodes meet to send each other message, while contact time corresponds to how much data two specific nodes can exchange during each contact. In previous studies, Inter-contact time and contact time distribution are employed to characterize the various real mobility traces or synthetic models.

There are several different opinions on the distribution of inter-contact time and contact time of real mobility traces. An early study of real human mobility is presented in [9], where they observed the inter-contact time is well approximated by a power-law over the range [10 minutes, 1day]. Their observation is confirmed using eight distinct experiment sets. In [10], author presents that the inter-contact time distribution of 90% contacts of mobile bus nodes approximately follows an exponential distribution. For a wide range of mobility trace, Karagiannis et al [8] show the inter-contact times are only power-law distributed up to 12 hours, and have an exponential cut-off after that. A possible course for this observation is the daily periodicity people have.

Han Cai et al. [11] show that simple random mobility models on boundless area can produce a power-law distribution of inter-contact times. They also show the exponential cut-off effect is in many cases a side-effect of bounded area. We believe even if simple random mobility model on boundless areas can produce power-law, it does not necessary show the general properties of real human mobility, as the human mobility is in fact most likely within a bounded area. The assumption of boundless area is not realistic.

Author [12] proposes a social network based mobility model. This model is based on the idea that node prefers to move to areas with higher social attractivity. The social attractivity is defined as the number of friends in a specific square. Friends can change periodically depends on the time of the day, for instance node meets colleagues as friends in the day and meet their family as friend instead in the evening. The paper does not show the inter-contact time distribution behavior for more than roughly one third of a day. Also, the model does not capture the essential properties such as *node and space heterogeneous*.

In [13], a community-based random walk model is presented. Community is defined as a set of frequent visited physical places. In a concentration period, node visit home community more often than other places. In normal period, nodes pick up community uniformly with equal probability. In contrast, our work assumes node has a list of frequent visited places and a list of less frequent listed places. Then, we define community as node with similar mobility patterns which are determined by the set of most visited places. In other words, our community is node centric, rather than the physical place centric. Moreover, in [13] authors do not show the inter-contact time and contact-time distribution and their comparison to real mobility trace.

3. Heterogeneous Community-based Random-Way-Point Model

In this section, we firstly present several key properties of human mobility based on intuitive observations of real human mobility and analysis of real mobility traces. Then we describe the HC-RWP model in details and show how the model captures the properties of real human mobility.

The intuition of real human mobility is that: node visits a few locations very frequently while only occasionally visit other locations. We refer this property as *space heterogeneousness*. Besides, different nodes may have very different mobility pattern i.e. nodes have different most frequently visited places. We refer this property as *node heterogeneousness*. The third property is that human mobility tends to show *(short-term) time heterogeneousness*. The set of frequently visited places could be different at different periods of the day. For example, in day time, office lady more often stays at her office, while in the evening time she more often stays at home with her family. Lastly, human mobility pattern are repetitive every one or multiple days, e.g. with the high probability, she re-visits the same set of places regularly. This is also called *(long-term) time periodicity***.** Besides the intuitions of real human mobility, the real trace analysis [5] [6] indeed confirms the above mentioned properties. By studying the real user traces, they found that that node only visit few WLAN APs in campus areas. They also show nodes mobility while using the network is very low and one node only meets a small portion of all other nodes in the area. Finally, they also show the repetitive patterns of node movement with a period of one day and heterogeneity among nodes.

In HC-RWP, to model the *space heterogeneousness***,** for each node we define the *home location* as a set of most visited places and *roam location* as a set of less visited places. For simplicity, we model *home location* and *roam location* of one node from set of discrete places into a continuous area which covers those places. Thus, *home location* of one node is an area that covers its most frequent visited places for given time interval T_j:

$$H^i(T_j)\text{, for node i}$$

roaming location of one node is an area that covers its less frequent visited places at time interval T_j:

$$R^i(T_j)\text{, for node i}$$

Different node i have its own *home location* and *roam location,* which captures *node heterogeneousness.* Furthermore, the *home location* and *roam location* of one node are updated on different time interval T_j , which captures *(short-term) time heterogeneousness*. Finally, the updates of *home location and roam location repeat* periodically over a period **T** e.g. one or multiple days, which captures the *(long term) time periodicity.*

To give a clear presentation, we present a simplified version of HC-RWP. We classify the set of nodes that have the same *home location* and *roaming location* (thus identical mobility pattern) as one community. Assume the number of node is ***N***, the number of communities is ***X***, and set of nodes of community i is C_i, the following holds:

$$\sum_{1}^{X}|C_i| = N\text{, where } |A| \text{ denotes the cardinality of finite set A.}$$

Node movement is modelled into two states: “home” state and “roam” state. In “home” state, nodes of community i move or stay within area home location. In “roam” state, nodes of community i move or stay within roam location. Nodes travel between “home” and “roaming” states which can be characterized by a two-state Markov Chain model showed in Markov transition diagram in figure 1. The details of node movement are as follows:

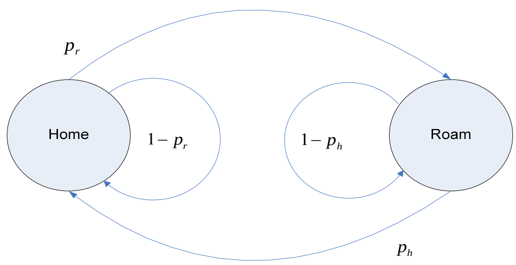

Figure 1: HC-RWP Model

As shown in figure 1, we denote the π_h^i as the probability that node is in a "home" state and π_r^i as the probability that node is in a "roam" state. From elementary Markov chain theory, for node in community i, we get the following:

$$\pi_h^i = \frac{p_h^i}{p_h^i + p_r^i} \text{ and } \pi_r^i = \frac{p_r^i}{p_r^i + p_h^i}$$

We also defined two terms "home trip" and "roam trip"

- Home trip is a random way-point movement towards a point in home location, i.e. either a random way-point movement within home location, or a random-way point movement from roaming location to home location. To be specific, node picks up a point uniformly sampled from home location area and moves towards it with a constant moving speed. Upon reaching it, pause for a constant duration.
- Roaming trip is a random way-point movement towards a point in roam location, i.e. a random way-point movement inside the roaming location or from home location to roaming location. To be specific, node picks up a point uniformly sampled from roam location area and moves towards it with a constant moving speed. Upon reaching it, node pauses for a constant duration.

We assume the period **T** is one day (excluding node sleep time in the night) which is divided into two periods: day time period T_1, evening time period T_2 [10]. We assume the global area ***M*** is a large square consisting of ***K*** small squares (grids) m_j, *j=0, 1, 2…K*, the following holds:

$$M = m_1 \cup m_2 \cup m_3 ... \cup m_K ,$$

For the period T_1, nodes of community i is pre-assigned one grid out of ***K*** grids as the *home location*. Nodes of community i is also pre-assigned one grid as *roam location.* For the period T_2, we follow the same instruction of assigning home and roam location as in T_1. Without loss of generality, we describe an algorithm that implements Waypoints Selection function of HC-RWP for community i. All other communities follow the same instructions. The algorithm is shown in *Algorithm 1*:

[10] In principle, it can be divided into more than two time intervals. Here, two interval is only for simplicity

ALGORITHM 1

INITIALIZATION:

- Assignment of home and roam location for community i:

$$H^i(T_1), R^i(T_1), H^i(T_2), R^i(T_2)$$

- Locate initialized positions of nodes of community i such that node position distribution corresponds to the time-stationary distribution of HC-RWP model, employing sampling algorithm of Perfect Simulation [7].

ALGORITHM

Input Parameters**: *simulation_time*** is the current simulated time; C_i is the set of nodes belong to community i; **T** is the period during which node repeat the same mobility.

Way_Points_Selection (*simulation_time*, C_i**)**

If ((***simulation time*** mod **T**) $< T_1$) {

For each node of community i, select next movement:

If (node is in "home" state), the next movement is a home trip with probability $1 - p_r^i$, or a roaming trip with probability p_r^i.

If (node is in "roam" state), the next movement is a roaming trip with probability $1 - p_h^i$, or a home trip with probability p_h^i.}

If ((***simulation_time*** mod **T**) $= T_1$) {

For each node of community i:

Re-set the home location to $H^i(T_2)$;

Re-set the roam location to $R^i(T_2)$;}

If (T_1 =< (***simulation_time*** mod **T**) $< (T_1 + T_2)$) {

For each node of community i, select next movement:

If node i is in "home" state, the next trip is a home trip with probability $1 - p_r^i$,

or is a roaming trip with probability p_r^i.

If node i is in "roam" state, the next trip is a roaming one with

probability $1 - p_h^i$, or a home one with probability p_h^i. }

If ((***simulation_time*** mod **T**) $= (T_1 + T_2)$) {

For each node of community i:

Re-set the home location to $H^i(T_1)$;

Re-Set the roam location to $R^i(T_1)$;}

END

4. Simulation and Validation

In this section, by discrete event simulation, we firstly show HC-RWP model well captures the observed properties of real human mobility. Then we validate the statistic features of HC-RWP model by comparing the collected real mobility trace.

We implement HC-RWP in our own simulator in C language [4]. The simulator is based on a simple communication model: two nodes can communicate with a nominal bit-rate if their geometric distance is smaller than a threshold value. This geometric distance is set to 40 meters (outdoor radio range of 802.11b). We consider the following setting of HC-RWP model. We assume 100 mobile nodes are equally grouped into four communities C_1, C_2, C_3, C_4.We assume the global area M is a large square with diameter [1500 m, 1500 m] consist of four small squares (grids), m1, m2, m3 and m4 and five intermediary areas, as shown in figure 2. Each of the grids is [500 m, 500 m] size. These four grids are physically separated by intermediary areas, yet nodes can pass by those areas to reach any grids. For the preliminary study, the simulated time is set to 16 hours which corresponds to one day time period T_1 (8 hours) and one evening period T_2 (8 hours). During both T_1 and T_2, the home location and roam location of community i are pre-determined before simulation and summarized in the table 1:

Table 1: Definition of Communities

Community	Home location $H^i(T_1)$	Home location $H^i(T_2)$	Roam location $R^i(T_1)$	Roam location $R^i(T_2)$
c_1	m1	m2	m2	m1
c_2	m2	m3	m3	m2
c_3	m3	m4	m4	m3
c_4	m4	m4	m4	m4

As in the table, we assume the *home location* of T_2 *is* pre-assigned with *roam location* of T_1, while *roam location* of T_2 is assigned with *home location* of T_1. In other words, every node swap the home and roam location regularly every T_1 or T_2.

Furthermore, we assume the transition probability between "home" and "roam" states in fig 1 are the same for all communities and are defined specifically in various scenarios

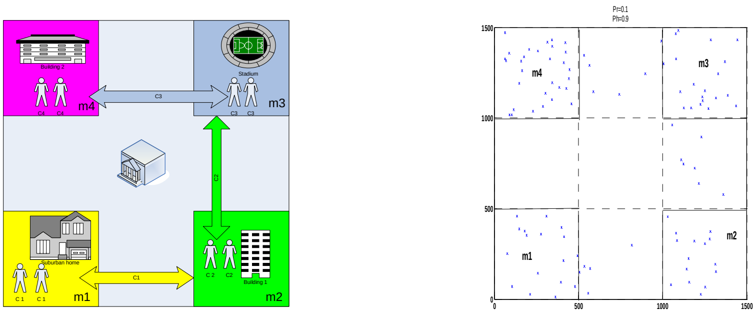

Figure 2: HC-RWP model with four grids and four communities

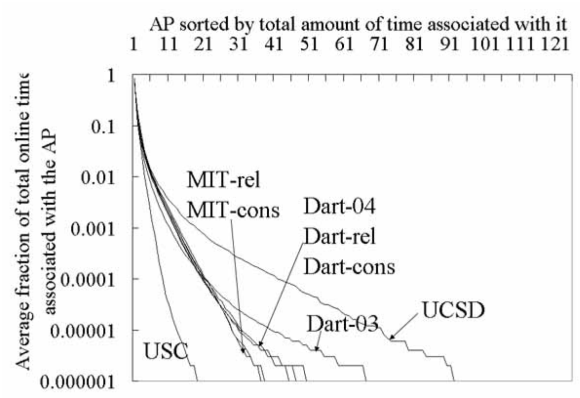

Figure 3 (a): Average fraction of time a mobile user associated with APs. For each user, the AP list is sorted based on association time before taking average [14].

The first step is to validate the observed properties of real human mobility: *node heterogeneousness, space heterogeneousness, (short term) time heterogeneousness*. According to observations in [14], for a wide set of mobility traces of wireless LAN on university campuses, each user spent most of its time associated with very few Access Points (APs). In particular, as showed in figure 3(a), for all the traces they studied, on average each mobile user spends more than 65% percent of its time (they called it online time) associated with one AP, while more than 95% of its time associated with only 5 APs. This observation confirms and inspires the *space heterogeneousness* of our model.

To validate the *space heterogeneousness*, we divide the whole simulation areas into 36 equal size grids. Each grid is covered by one of the 36 virtual Access Point (AP). Each AP keeps track of the time duration that nodes stay within its coverage area (aggregate time duration over all nodes). In other words, we keep records of aggregate fraction of time over all nodes that stay within the each of 36 sub-areas of the whole square. The mapping between sub-squares and AP index is presented in table 2:

Table 2: Access point index

Square	AP Index
m1	1, 2, 7, 8
m2	25, 26, 31, 32
m3	29, 30, 35, 36
m4	5, 6, 11, 23

In figure 3(b) (c), we show HC-RWP can capture several properties of real human mobility: *space heterogeneousness, node heterogeneousness, time heterogeneousness.* In fig 4(b), y-axis shows the aggregate time duration that nodes stay within the coverage area of each AP at period T1, while the x-axis shows the AP index. It is clear from fig 3(b) that, for all the four communities, nodes visit some AP coverage areas of home location much more often than other AP coverage areas, which captures *space heterogeneousness*. Also, nodes of different communities have different set of frequent visit areas or home location, e.g. nodes of c_1 mostly visit AP1, 2, 7, 8, while nodes of c_2 mostly visit AP 29,30,35,36, which captures *node heterogeneousness*. Finally, fig 3(c) shows the aggregate time duration that nodes stay within the coverage area of each AP at period T2. We observe that each of the community exchange its home location and roam location, compare to the case of period T1. For instance, during period T2, nodes of C1 mostly visit AP 25,26,31,32 while they only occasionally visit AP 1, 2, 7, 8. During period T1, nodes of C1 mostly visit AP 1, 2, 7, 8 while they only occasionally visit AP 25,26,31,32. In this way, the HC-RWP captures *time heterogeneousness* of real human mobility, i.e. nodes have time-variant home location and roam location. Of course, dividing one day into two periods T1 and T2 is a low granularity approximation of time-variant real mobility pattern. A more accurate version of the model could be developed by dividing one day into multiple periods (larger than two).

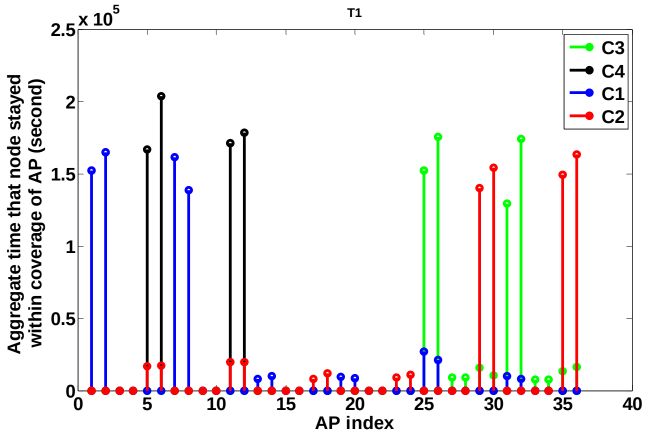

Figure 3 (b): Time duration that each community stay within the coverage area of each AP at period T1

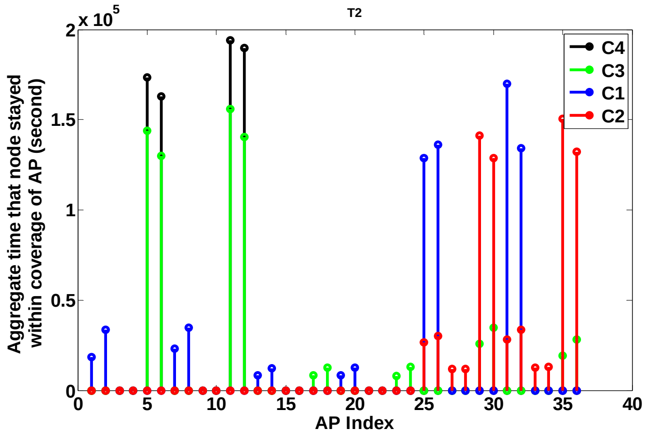

Figure 3 (c): Time duration that each community stay within the coverage area of each AP at period T2.

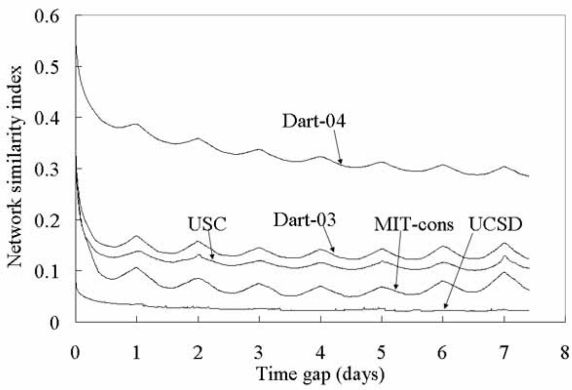

Figure 3 (d): NSI curves with smaller absolute values (less always-on, stationary users) [14]

In [14], they also revealed that, with very high probability, mobile users tend to repetitively visit the area covered by the same AP in a time period of multiple days, for most traces. In particular, they looked into the Network Similarity Index (NSI), which is essentially the probability that any user revisit the same AP after a certain time break. As shown in figure 3 (d), in most traces (expect for UCSD trace), the NSI is higher if the time break is close to integer of multiple days or even a week. This confirms and inspires the *long term time periodicity* of our model. UCSD trace does not show obvious time periodicity, because the user population are PDAs which are used only in a casual way with a short and sparse online duration.

In fig 3 (e), we validate that HC-RWP captures the time periodicity of real human mobility pattern, which is the fourth observed property discussed above. Here we assume the simulation time is 32 hours and the period T is 8 hours consist of T1=4 hours and T2=4 hours. According to the algorithm 1 and definition of table 1, each community update their home location and roam location every 4 hours while the transition probability does not change. The y-axis is the aggregate time duration (per hour) over all nodes that stay within the coverage area of AP index 1 during the simulation time 32 hours. The unit of y-axis is second. It is obvious that aggregate time duration (per hour) that nodes stay within coverage area of AP index 1 is periodical with peak value roughly every four hours. The same observations remain if the set of T, T1and T2 are chosen other values.

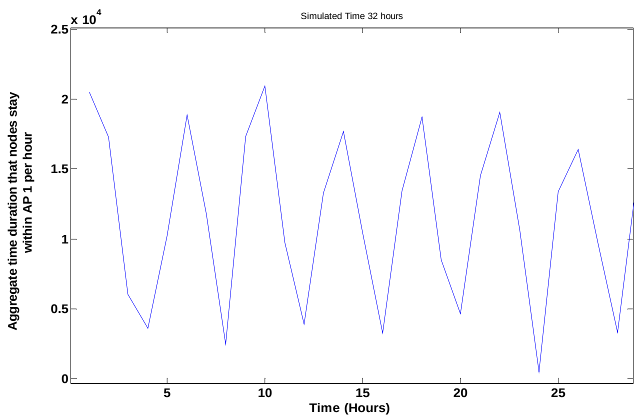

Figure 3 (e)

To validate HC-RWP model generates synthetic traces statistically similar to real mobility trace, we analyzed two metrics: the inter-contact time, defined as the time interval between two consecutive contacts between any two nodes; the contact time, defined as the time interval in which any two devices are in radio range. We compare the inter-contact time and contact time with real traces.

Despite there have already been some analysis of real human mobility traces, the distribution of inter-contact and contact time of real human mobility is still not clear, because of the limited available real traces, e.g. low data granularity, small number of experiment participants. In [9], authors claimed CCDF (complementary cumulative distribution function) of inter-contact time follows power-law, while authors in [8] claim it follows power-law with exponential cut-off. In [10] authors show the CCDF of inter-contact time of real bus mobility traces follows exponential decay.

Under HC-RWP model, we investigate CCDF of inter-contact time between mobile nodes under the impact of various transition probabilities p_h^i and p_r^i defined in section 3. In figs 4(a) (b), we show that CCDF of the inter-contact time on log-log and line-log scales. The simulation time is 32 hours and the period T is 8 hours consist of T1=4 hours and T2=4 hours. The simulation parameters are as follows in table 3:

Table 3: Simulation Parameters

Moving Speed	Pause time	(p_h^i, p_r^i)
1 m/s	100, 600, 1200 second	(0.9,0.1) (0.6,0.4)

Firstly, fig 4(a) (b) show the CCDF of inter-contact time (for all parameter values) approximately follows exponential distribution, which is in line with the analysis of real mobility traces presented in [10] and [8]. Secondly, we observe that, for the given P(r) = 0.1, P (h) = 0.9, the pause time does impact the inter-contact time distribution. In particular, larger pause time (e.g. 1200s) incurs larger inter-contact time on average than small pause time (e.g. 100 s and 600 s). This trend is nature, as pausing nodes produce longer contact durations but less frequent node meetings. Secondly, for a given pause time 600 second, fig 3 (a) (b) show transition probability (P(r) = 0.4, P (h) = 0.6) on average gives larger inter-contact time than transition probability (P(r) = 0.1, P (h) = 0.9). This is because node tends to move around a larger area with transition probability (P(r) = 0.4, P (h) = 0.6), which introduce a longer inter-contact time. On the other hand, node moves more locally with transition probability (P(r) = 0.1, P (h) = 0.9). Nodes that move around a larger area tend to less frequently meet each other, compared to the case of moving within a smaller area.

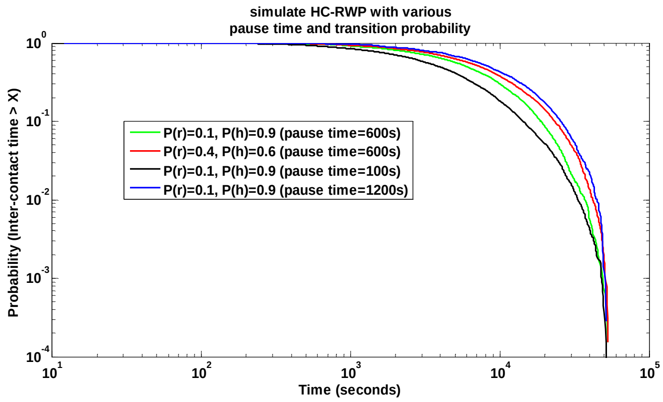

Figure 4 (a): Inter-contact time in log-log scale

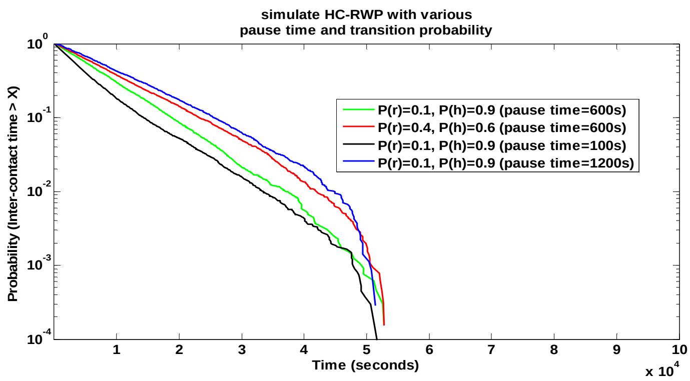

Figure 4 (b): Inter-contact time in line-log scale

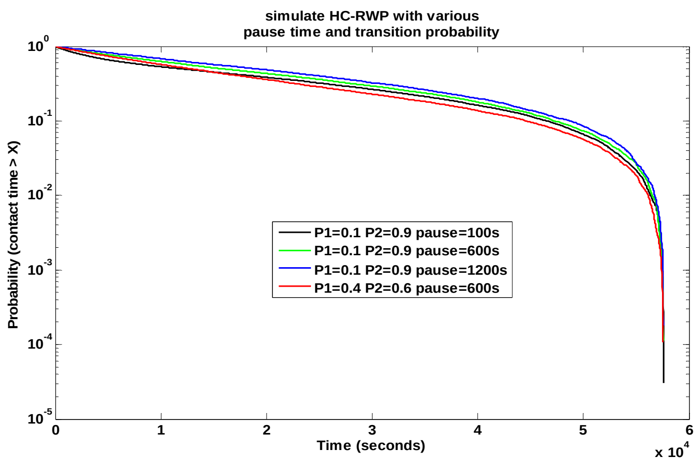

Figure 4 (c): contact time distribution in line-log scale

In fig 4(c), we show the CCDF of contact time in line-log scale. For most nodes contacts, the CCDF of contact time approximately follows exponential distribution under all parameters.

According to the above analysis, we claim that HC-RWP does capture statistic features of some real mobility traces [8] [10] in terms of inter-contact time distribution. It is the future work to tune the parameters of HC-RWP model so as to capture statistic features of other real mobility traces with different inter-contact time and contact time distribution such as [9]. On the other hand, more useful and thoroughly validation and tuning of HC-RWP can only be useful upon the availability of large-scale and high time granularity real mobility traces and their analysis in the future.

5. Conclusion and Future Work

We present a new synthetic mobility model HC-RWP for mobile opportunistic networking research area. By discrete event simulation, we show it captures four properties of real human mobility: *node heterogeneousness, space heterogeneousness and (short term) time heterogeneousness, (long term) time periodicity.* Those four properties are observed according to daily intuitions of real human movement and confirmed by the measurements of real mobility traces. Besides, in terms of inter-contact time and contact time distribution, we show HC-RWP does provide synthetic traces that have the same statistic features as some real mobility traces.

As the future work, we intend to extend our model to capture higher granularity time-variant node mobility, e.g. divided one day into more than two time periods, each of which have different mobility pattern. Also, we plan to tune system parameters of HC-RWP such that it can well match statistic features of all existing real mobility traces. Finally, as the current real mobility trace is rather limited, we look forward to validating and tuning our model upon the availability of large-scale, high time granularity real mobility traces in the future.

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