2015

Opportunistic Networks in Campus Environments

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OPPORTUNISTIC NETWORKS IN CAMPUS ENVIRONMENTS

by

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A thesis submitted in partial fulfillment of the requirements
for the degree of Master of Science
in the Department of Computer Science
in the College of Engineering and Computer Science
at the University of Central Florida
Orlando, Florida

Fall Term
2015

Major Professor: Damla Turgut

ABSTRACT

Opportunistic communication is an active research area in wireless sensor networks. Exploiting the opportunities to communicate between devices in an unstable network is one of the main challenges of the opportunistic communication. In this thesis, we propose an infrastructure-independent opportunistic mobile social networking strategy for efficient message broadcasting in campus environments. Specifically, we focus on the application scenario of university campuses. In our model, the students' smartphones forward messages to each other. The messages are created spontaneously as independent events in various places of the campus. The events can be either urgent security alerts or private announcements to the students who are currently on the campus. Our proposed state-based campus routing (SCR) protocol is based on the idle and active states of the students in indoor and outdoor environments. The proposed model is analyzed through extensive network simulations using mobility datasets collected from students on University of Milano, University of Cambridge and University of St Andrews campuses. The opportunistic network model and the SCR protocol is compared with epidemic, epidemic with TTS (Times-To-Send), PROPHET(Probabilistic Routing on History of Encounters), NDAO (Nodes Density Aware Opportunistic) and random routing protocols. We observe that the message delivery performance of SCR is close to Epidemic, PROPHET and NDAO while SCR reduces the amount of message transmissions.

ACKNOWLEDGMENTS

First of all, I would like to thank my advisor Dr. Damla Turgut for her support on my Masters Degree education. I would like to thank my committee members Dr. Mostafa Bassiouni and Dr. Ratan Guha for accepting my offer to be in my thesis defense committee.

I would like to thank Gürkan Solmaz for his help and support on my thesis. He has done a good job for making me accustomed to academic writing and research.

Lastly I would like to thank my friend Akif Özsoy for encouraging me to finish my masters education.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1
INTRODUCTION

Opportunistic networks are the type of ad hoc networks whose main assumption is that end to end connection between two nodes may not be possible at all times. Stable network architecture is not expected. The communication between nodes are mainly carried out on encounters via Bluetooth or WiFi connections. Because of its structure opportunistic communication in a network is considered a good approach where Internet infrastructure does not exist or is not usable.

In opportunistic networks, nodes may enter or exit the network at any time so the routing strategy of an opportunistic network should handle these condition and should aim to exploit the opportunities to forward a packet as much as possible. While designing the routing strategy, the researcher should also try to decrease the receiving delay of a message for all nodes and increase the distribution rate of a message through the network. in order to optimize energy usage, the number of packet sent should be decreased as much as possible. Excessive packet sending may decrease the delay and increase the distribution rate while having an impact on energy efficiency of the system.

Opportunistic social networks are becoming popular especially in mobile wireless networks. In the social mobile networks, the users are expected to use mobile devices or preferably their smartphones as a communication device. Most of the application scenarios of opportunistic networks covers the situation where the users are using laptops or mobile phones for communication in the opportunistic network research domain. Some application scenarios (i.e. photo sharing between people [1],health care application [2]) have been studied for users using laptops or smart phones. As an opportunistic forwarding environment, people's social life in a limited area (i.e. cities, university campuses, malls) may be considered. In a campus scenario, people will be entering and exiting the campus at the different times of a day. They will be walking between classes and food courts and they will be mostly on foot. In an example of a city, people will be pausing at stores and restaurants and walking between parking lots or just strolling around. Unlike an university campus, people will be also using bicycles, public transportation and their private vehicles frequently.

Recent advances and the increasing popularity of mobile devices allowed various applications of opportunistic social networks. Opportunistic networks are considered as a type of ad hoc networks and data transfer occurs in a hop-by-hop manner among mobile devices during encounters via Bluetooth or WiFi connections. The topology of these networks change frequently due to frequent addition or removal of the nodes. Moreover, data forwarding decisions during encounters have critical importance in the network performance. For instance, forwarding data in each encounter may cost the network excessive energy consumption, while limiting data transfers may prevent messages to arrive at their destinations.

There are two distinguishing characteristics of routing methods in opportunistic networks from the methods in conventional wireless networks. The first is related to the cost of links discovered by the routing algorithm which are supposed to remain constant in traditional wireless network settings. Some traditional routing approaches focus on discovery of the network structure before transmission of packets. In opportunistic routing approaches, however, it may not be possible to calculate all the routes to the destinations due to the dynamic nature of the network. The precalculated node distances may change as the nodes are mobile. The second characteristic is that the traditional routing protocols mostly consider connected networks. On the other hand, in opportunistic networks, nodes may become disconnected due to mobility of a walking person or a vehicle [3].

Our application scenario covers the example where messages are broadcasted on a university campus. The messages are created in various regions of a campus such as department buildings or current locations of the patrolling security personnel. We basically consider the situation where a message is created as an *event*. The events are spontaneously occur in random times of the day due to security reasons such as fire alarms, weather alerts (e.g., hurricane alert), closed roads, and so on. Moreover, the events can be private announcements that are only delivered to the students in the campus such as a parking lot closure, or a traffic accident. The smartphones of the students are used for hop-by-hop wireless transmissions. Each message has an expiration date according to the type of event. If the message is expired, it is not forwarded to any other node.

We are mainly focused on scenario-specific routing because we believe that a routing strategy based on an application scenario and environment will be more realistic and practical to use. We have used the characteristics of campus environment while designing the routing strategy. For the stated application scenario we have developed *State-based Campus Routing* (SCR) approach where the nodes change their message delivery probabilities according to their states. Keeping into account that people walk between buildings or stay in buildings (for classes, eating, studying etc.), the nodes change their state based on their encounters. The nodes can be either in idle or active state during their lifetimes. The current states of the nodes are based on the regions the nodes are located such as hot-spots or deserted areas. The efficiency of the proposed network model and the SCR strategy is compared with epidemic, epidemic with TTS(Times To Send), PROPHET [4], Nodes Density Adaptive Opportunistic (NDAO) routing [5] and random routing protocols using mobility datasets from University of Milano, University of Cambridge and University of St Andrews.

1.1 Motivation

Most of the previous work in opportunistic networks aim for a generic routing methods which are applicable to various scenarios such as the most popularly used epidemic routing [6]. As nodes drastically change [7] the network performances and mobility depends on the environment, we consider mobilities in specific scenarios. For instance, a person in an urban area may use a car or take a bus to go to work. On the other hand, in university campuses, vehicle use is mostly limited and students spend time in preplanned locations such as classrooms or food courts and walk between these locations during the day. Furthermore, due to sharing common places and having more common interests, the number of encounters with the same students and the encounter durations between the pairs are mostly expected to be higher.

While in this study we focus on the university campuses as an application scenario, our routing protocol can also be used in similar environments such as the large corporate campuses or theme parks where routine activities are mostly taking place. Some routing protocols require previous encounter information of the nodes in the network. For some routing protocols such as PROPHET [4], *ASSORT* [8], *DISCUSS* [9],*dLife* [10], nodes exchange their neighbor node's encounter history between each other which may increase the number of packets sent or complexity of the system. Our method differs from these models in the sense that routing does not require prior knowledge about the system.

1.2 Contribution

The contributions of this thesis are as follows.

- We have defined an application scenario for opportunistic communication. Previously developed routing strategies on campus environment data (i.e. [11], [12], [13]) but they did not define application scenario for their work. We defined an application scenario for our routing strategy and explained other feasible application scenarios where our system can be implemented.

- We have proposed a lightweight routing protocol that does not require any packet exchange between nodes besides the actual messages. Some of the proposed routing solutions require nodes to collect id of their past encounters. Besides that, there are also approaches where nodes exchange encounter history related information (i.e. [4], [11]) or collect device holder's private information (i.e. [14], [15]). We have defined a routing strategy that no information about the past neighbor node is stored in the wireless nodes. In that way, the system can be applied to an environment that has many nodes. Since IDs of the previous neighbors are not stored by the nodes, our system can be applied to application scenarios where keeping track of the nodes entering the opportunistic environment is not possible because of technical or security related issues.

- We have proposed a routing strategy, State-based Campus Routing (SCR), that is as successful as epidemic, which is considered as optimal in terms for delay and success rate, but sends less packets than Epidemic. SCR keeps the message delay and success rate close to epidemic whereas decreasing amount of packets sent about 10% to 20%.

1.3 Organization

Chapter 1 presents the motivation, the problem definition, the contributions and the organization of the thesis. Chapter 2 provides a review of the literature related to routing, campus routing and opportunistic communication. We described the application scenario, opportunistic commmunication environment and SCR for campus environments in Chapter 3. We presented the results of the simulation runs for SCR comparing with other routing strategies using University of Milano, University of Cambridge and University of

St Andrews mobility walk trace dataset in Chapter 4. Chapter 5 concludes the thesis and summarizes the results.

CHAPTER 2
RELATED WORK

2.1 Routing Protocols

Let us briefly summarize the related literature on opportunistic routing strategies. Vahdat and Becker [6] propose epidemic routing as the flooding approach in opportunistic routing. Epidemic routing provides minimum message delays and maximum success rate in the case where nodes have unlimited buffer capacities. There are routing strategies experimented with data collected from university campuses. These routing strategies mostly require nodes to share their collected network information with each other. PROPHET routing model, proposed by Lindgren et al. [4], is an example of such routing strategies. SCR does not require this type of data exchange as routing protocols that require sharing network information between nodes bring energy overhead and excessive message traffic.

Most of the routing strategies examined under routing protocol heading either use random mobility (i.e. [16], [17], [14], [18], [19], [8], [20]) for the nodes or do not state any result related to energy usage (i.e. [21], [14]). Rohankar [17] has developed a technique for calculating contact probability of two nodes at a specific time. Rohankar has used that technique as an opportunistic routing in an environment where node movements were cyclic but randomly modeled. Chen et al. [21] modified Dijsktra's classical algorithm to propose

MC-DHCD routing algorithm. Chen et al. [21] has presented some results about delay and throughput but did not give information about energy usage or make a comparison with other routing techniques. Karyakarte et al. [18] has proposed a routing scheme in opportunistic networks. Unlike SCR, their strategy was mainly about the link layer in the network and simulation time was 50 seconds which is rather short. Rango et al. [14] has used Facebook information: therefore, Internet in their routing strategy in an opportunistic environment. They have used Sigcomm 2009 conference Bluetooth encounter dataset [22] and they found that the message delay was higher than epidemic in their study. Mao et al. [16] has proposed *Energy-Efficient Opportunistic Routing (EEOR)* which sends less packets than *ExOR* routing and lower delay rate than ExOR routing. Mao et al. did not provide success rates and compared only with ExOR. Another concern for *EEOR* was that the opportunistic network environment was dense so that the network will probably stay connected at all times. Also the node mobility model in simulation network for EEOR was random. Hsu et al. [8] has suggested ASSORT routing strategy, based on sleep-wake scheduling for energy utilization. Hsu et al. has tested ASSORT on synthetic data and compared with EFFORT [19] which is energy-efficiency based routing scheme. Energy efficiency of EFFORT is measured with network life time. Guo et al. [20] proposed opportunistic flooding technique in low-duty-cycle wireless sensor networks where node communications were not ad hoc. Guo et al. [20] used synthetic data and no performance comparison with other routing techniques are conducted.

There are also routing schemes where nodes need position information (i.e. [23]) or need to exchange data between each other while sending actual messages (i.e. [4], [8], [9],

[15], [10]). Misra et al. [9] proposed a *Distributed Information-Based Cooperation Ushering Scheme (DISCUSS)* to promote cooperation in message forwarding between nodes in an opportunistic network. Similar to SCR, *DISCUSS* is also tested on University of Milano human walk trace dataset. Unlike SCR, nodes interchange their past history (own delivered message list and nodes' delivery probability list) with the neighboring nodes. Moreira et al. [10] propose *dLife* routing method using daily life activity information based on the Helsinki city trace data. The trace data contains human walk and vehicle mobility traces. Our strategy is different from the aforementioned work in terms of the application scenario of broadcasting messages created by the events. Aviv et al. [23] proposed Probabilistic Profile Based Routing to efficiently routing messages in opportunistic networks while keeping the privacy of the users. Unlike most opportunistic networks, in their approach the routing algorithm should know the local density of the nodes in the network and every node should also be able to get its position (i.e. GPS) accurately. Our approach does not require position information and any excessive data exchange between nodes compared to many of the existing literature.

2.2 Campus Environment

Su et al. [12] provide Link State opportunistic routing strategy using campus data. Link State routing strategy requires nodes to exchange their link state weights with each other besides their messages. 3R routing [13] requires nodes to learn the encounter pattern of the network before sending packets which may not fit a case where immediate message delivery is required in the campus environment.

Song and Kotz [11] proposed a routing strategy in which nodes calculate the sending probability based on contact frequency in a campus environment. Their strategy requires more packet transmissions than PROPHET, but less than epidemic, whereas SCR sends less packets than epidemic and PROPHET. Srinivasan et al. [24] study epidemic routing on synthetically generated campus mobility data based on students' lecture schedules.

Feng and Chin [25] experiment different variations of the epidemic routing in campus environments. Lu et al. [5] propose *Nodes Density Adaptive Opportunistic (NDAO)* forwarding protocol where a node sends packets if its number of neighbors is above a threshold value. Although *NDAO* produces satisfactory results for delivery ratio and latency, the energy overhead is not studied. Liu and Wu [26] has studied *Optimal Opportunistic Forwarding(OOF)* routing strategy on Cambridge human mobility and UMassDieselNet bus mobility data. They compared OOF with epidemic, SprayAndWait, MaxProp and Delegation routing techniques. Xiao et al. [27] has proposed *Community Aware Opportunistic Routing* and used Dartmouth College WiFi trace data. Chen and Shen [28] used *StaticWait* routing to implement a mobile content sharing system where the motivating problem in their case was content replication for data sharing. They have used Bluetooth encounter datasets of Darthmouth College, MIT and InfoCom conference.

Gao et al. [29] developed a technique that decreases the amount of redundant messages forwarded by CCP, PROPHET and SprayAndWait routing strategies in opportunistic networks. Gao et al. has experimented on University of California at San Diego dataset where users were using WiFi and connecting via access points. Han et al. [30] has proposed a device discovery protocol for opportunistic networks, *eDiscovery*, aims to decrease the energy usage in neighbor discovery process of a node. *eDiscovery* is experimented on Student Union of the University of Maryland however the experiments were 30 minutes long. *eDiscovery* is also not a routing and communication oriented protocol; however, it examines the opportunistic communication problem in a different point of view. Vieira et al. [31] has used Dijsktra's shortest path finding on graph algorithm while analyzing the mobility datasets including University of Milano and University of St Andrews. Vieira et al. [31] mainly aimed at analyzing the metrics of the datasets rather than proposing an application or routing protocol.

2.3 Opportunistic Communication

Although there are several opportunistic routing strategies in the literature, the applications of opportunistic routing types are limited. Haggle [1] project covers various applications of opportunistic network application along with a routing strategy. PhotoShare [1] is a mobile application implemented under Haggle project aims for people to share photos between each other using smartphones. People can tag photos while uploading. The uploading and downloading actions took place between nodes in the opportunistic network. Hu et al. [32] has surveyed the applications of mobile social networks.

Papadopouli and Schulzrinne [33] proposed 7DS system to enable users share data via P2P. They used synthetically generated data from random waypoint model. Lindgren et al., [34] has applied their PROPHET routing scheme for a system in Laponia region in northern Sweden. In their application scenario, people are able to send emails, not so instant messages and surf the Internet with the help of opportunistic communication. In their case there was no continuous Internet access for any of the nodes.

Solmaz et al. [35] has studied Pcenter problem in theme parks for positioning nodes in a mobile wireless sensor network. Solmaz and Turgut has presented solution to event coverage problem which involves mobile nodes in a wireless sensor network [36], [37]. Solmaz and Turgut [38] has used epidemic routing with minor modifications while tracking pedestrians during evacuation of a theme park.

Zebranet [39] is another application of opportunistic communication that aims at monitoring habits of zebra activities by placing wireless devices on them as collars. Zebras carry each other's mobility data and upload when passing near a wireless data collecting station. The Pollen network was proposed by Glance et al [40]. This system consists of mobile devices and sinks. The system can be used in location tracking of the mobile devices or information gathering.

MIT Media Lab has developed DakNet where mobile access points and kiosks can exchange data [41]. DakNet mainly covers a case where only mobile access points are mobile and transmit data between kiosks. In our case, all of the nodes are mobile and can contact with each other. Conti et al. [42] provided a file sharing system between mobile nodes where HIBOp is used as routing algorithm. No comparison results between their strategy and other routing strategies stated in their work. Mahéo et al. [43], developed DoDWAN communication system that has built in message and file exchanging applications. DoDWAN relies on WiFi communication between netbooks using students and uses epidemic routing strategy. Specific metric results for their application case is not expressed in their work.

CHAPTER 3
STATE-BASED CAMPUS ROUTING (SCR) PROTOCOL

3.1 Campus Environment

The campus environments are the places where most actions happen according to daily routines. Daily activities of students and staff follow a routine. For instance, they go to classes at the predetermined times of the day, go to lunch and dinner in the food courts and sometimes go to cafeterias in the campus to have time with their colleagues or friends. People's weekly activities are also scheduled for every week. As an example, students and professors go to classes some specific days of the week.

Our opportunistic network model mainly focuses on the places that people's encounter frequency increases. We call these places hotspots. There are some characteristic hotspot locations in campuses where people's daily life activity in campus takes place. Some hotspot location examples are explained in below paragraphs.

Cafeterias are the places where people spend time with their friends and colleagues. People in university campuses usually go to cafeterias or restaurants at meal times (i.e. lunch or dinner). Apart from these times people can also go to these places to spend some time while waiting for the next lecture time. It is also possible that people go to these places after lecture times to spend some time with their friends. Gates or security locations are the places where people's encounter frequency increases. These are not pause locations but if the campus has a common gate or security checkpoint, it is likely that people will use these places to enter or exit the campus. These locations will be also crowded places in terms of Bluetooth contact range. To broadcast a message it will be useful to put the message flooding nodes at these places. Building entrances and exits are also good candidate points to be a hotspot. As people will always use exits or entrances to go inside a building, building doors will also be good points to put the message flooding nodes if they need to be put to some stable location. These buildings may be the classroom or department buildings as well as cafeteria buildings. Dormitory buildings may also be counted in this classification if the campus has such facility. If the campus has some dedicated laboratory buildings for scientific research, these type of buildings may be a good candidate. Student activity centers may be counted as hotspots. Sports centers, stadiums, tennis courts may be put into this activity center classification. People generally stay at these places for hours as sport activities generally takes longer than a meal time or even a lecture time. Libraries are examples of hotspot locations. Students or academical staff go to the library. Especially students are expected to stay at library longer than academical staff. Students may be going to library to spend some time between lectures or study there when their lectures finish. It is also possible that people will go to library to take part in some event in a campus as libraries may be used for public activity places (i.e. exhibitions, talks, conferences).

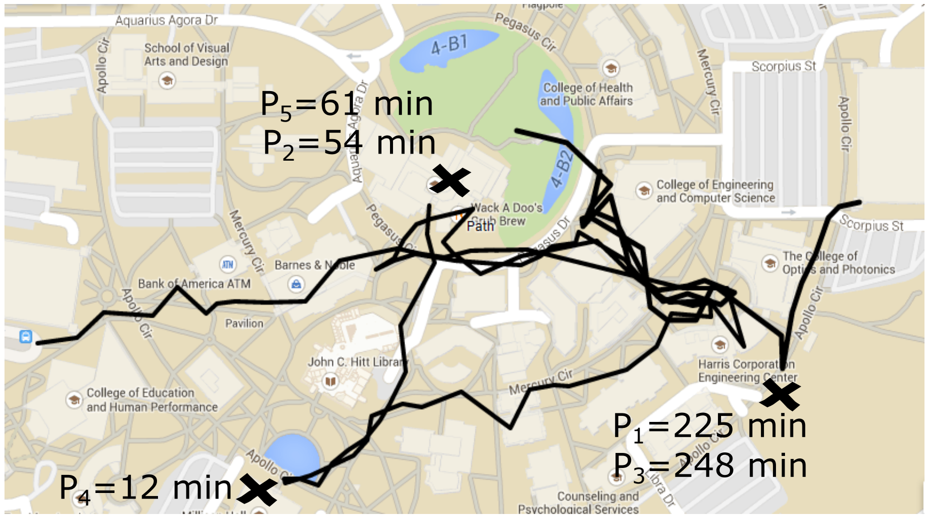

Figure 3.1: A daily walk trace of a student in the UCF campus

We collected mobility traces using GPS-enabled smartphones and observed the daily mobility patterns of the students from our research group. The database contains 18 days of walk trace. An example daily walk trace in the University of Central Florida (UCF) campus can be seen in Fig. 3.1. Figure 3.1 represents walk traces of a graduate student in campus. The waiting times in 5 pause locations near the trajectory lines are shown in the Figure 3.1. It can be seen that during the day the student goes to the laboratory (P_1, P_3), the lunch place (P_2, P_5) two times. Another pause location P_4 is in some building in the campus possibly where the student meets with a friend and then goes to dinner. Similar traces can be observed for the same day of each week.

3.2 Opportunistic Network Model

We consider an opportunistic social network where people in an university campus are using smartphones. In our application scenario, the messages are created by mobile nodes in the university campus when an *event* occurs. The events occur at random times during the day due to security reasons such as fire alarms, severe weather alerts or due to necessary announcements such as a closure of a pedestrian way. Advertising for student organizations' leaders can be done by our opportunistic social network in universities. For the advertising case, the creator of the messages can be specific students who are responsible for the group activities. For the disaster messaging system application case, the creator of the messages can be located in the departmental buildings or they can be security personnel patrolling in the campus.

A smartphone is a node in the network that receives a message, stores it and carries to the other nodes. The message transmission is handled by wireless communication of the smartphones in a hop-by-hop fashion using the Bluetooth and Wifi connections. The proposed network model does not require any infrastructure such as a base station or access point for message broadcasts. Therefore, it is useful for various conditions such as natural disasters which may damage the infrastructure and disrupt the service provided by Internet.

Although our main application case is a campus environment, the proposed model can also be used in large outdoor or indoor work areas. Some good application areas that our model can be applied are as follows:

While sharing announcements and advertisements in cities, our proposed model can be used. People may become aware of the discounts, activities, blood donations and public events. Main information source devices can be placed in some stable place (i.e. buildings) or the devices can be mobile. If that system is also supported by Internet, participants may be required to register as an information source. After registration, only the registered users will be able to create messages whereas all other users will be able to receive the messages without use of Internet. By this way, anonymity may be preserved more than the case where Internet is used. Mobile devices will use less energy as they do not need to be connected to some access point to receive messages. Yellow pages application can also be implemented based on our proposed model. Users can write messages about what they need to sell or buy with their contact information. These messages will be broadcasted to every place that the user will go. For this specific case, message delay will not be much important so opportunistic message broadcasting will be a suitable technique for yellow pages application. Discounts and event informations in shopping malls can be shared by customers by using this system. The customers will install some mobile application that will send them the discount information. Malls are crowded places. People also walk or sit at food courts as in the case with campus environment. People will stay at the stores similar to staying at classroom or library to study. Another application area for our model may be theme parks. Security officers and workers may have some mobile devices to communicate with each other. This communication system may be useful in emergency conditions. Security officials may lead people to evacuate the buildings or common areas after getting emergency messages. Theme park mobility has been studied by Vukadinovic et al. [44] and Solmaz and Turgut [45]. Surveys can be made with our opportunistic network model. Each user will send the survey questions and survey replies of other users to its neighbor users around. Once the user fills the survey on his/her mobile device, the mobile device will send the answers of himself/herself and the collected answers. Since the users are also carrying the answers of other users, they also will be able to get the statistics about the survey or surveys.

3.3 State Based Routing Protocol (SCR)

We propose an opportunistic routing protocol based on the campus environments, which we name *state-based campus routing* (SCR). In our routing strategy, we consider the fact that people mostly spend their time either waiting in the buildings or walking outside in the campus. The waiting locations such as classrooms or food courts are mostly crowded places with high encounter frequencies between pairs of nodes. When a person leaves the waiting location we expect that the nodes encounter frequency will decrease. In addition, based on the routine nature of the campus environments, the person may repeatedly encounter the same group of people, such as classmates. Another example might be the person seeing the same group of friends at the cafeteria at noon. The message transmission procedure (i.e., sessions) is similar to the epidemic routing [6]. Nodes act with either a sender or a receiver role. When two nodes encounter with each other, two nodes open a session. The sender node first sends the message vector (i.e., simply a packet that holds the ID of the messages that the sender has) to the receiver node. Each message has an expiration date. The receiver node replies by sending another message vector that holds the message IDs that receiver does not have. The sender then sends the messages whose IDs are stated in the previous transmission. The two nodes also switch their roles as sender and receiver and open a new session.

In our routing method, each node can be in either *idle* or *active* state. If the node encounters many nodes in a small period of time compared with its past encounter frequencies, then we suppose that the node is in a waiting place or in a *hot-spot*. In other words, idle state starts when time between encounters start to decrease as it is shown on Figure 3.2. Figure 3.2 shows an example of active states where time between encounters of a node starts to increase. If the node is in active state, it means that the node is either walking or at a some place where encounter frequency is lower.

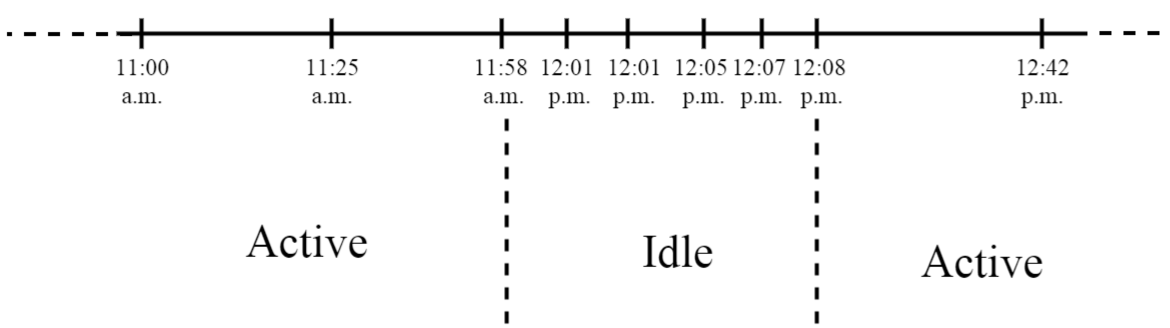

Figure 3.2: An example timeline that shows a mobile node's encounters.

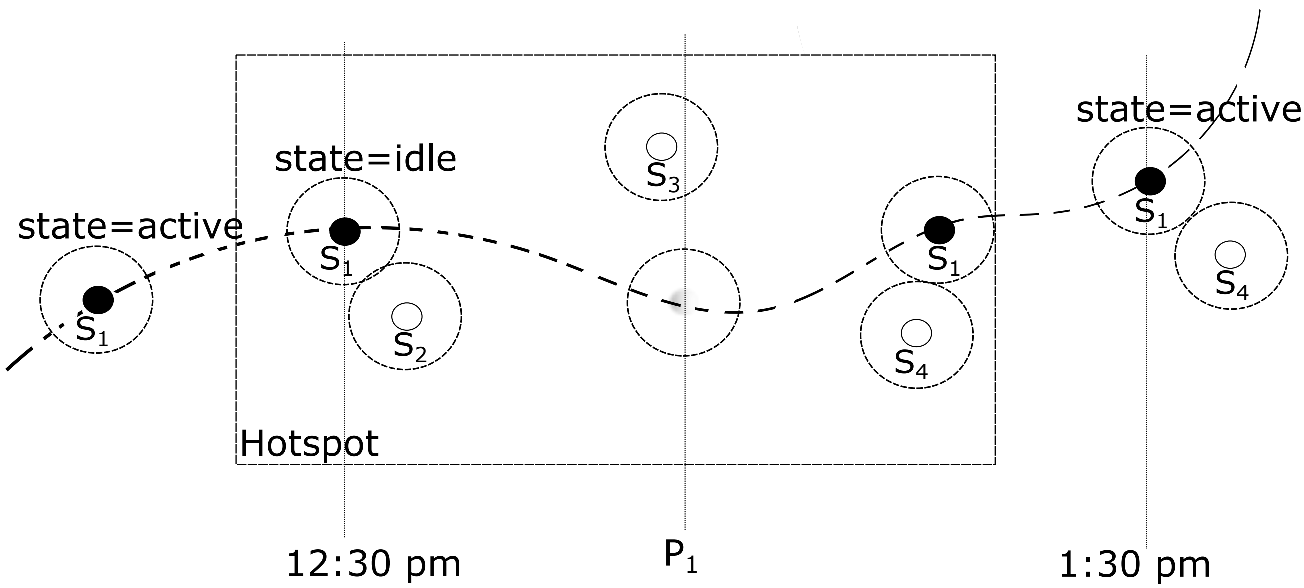

Figure 3.3: A mobile node entering into a hotspot, waiting at pause point P_1, and leaving the hotspot.

Fig. 3.3 illustrates the state changes of a mobile node for an example case based on the mobility traces we collected in the UCF campus. In the case shown in this figure, the node S_1 enters into a hotspot (e.g., food court, restaurant) to have a lunch at 12:30pm and encounters with another node S_2, which was already in the hotspot. S_1 later starts waiting at the pause point P_1. Before entering the place S_1 is in the active state and the node has higher probability of forwarding packets. When the node starts to encounter with other nodes such S_2 and S_3 in a short period of time, it changes its state to idle. In the idle state, probability of S_1 to forward packets decreases to prevent excessive packet transmission traffic in the hotspot. S_1 stays in idle state in the waiting time of one hour. When it leaves the hotspot, its state changes back to active. This means that S_1 is not encountering with as many nodes as it used to in the hotspot and therefore it should be actively forwarding messages whenever possible. The node's probability to forward packets increases in the active state and it will stay active till it gets to another hotspot. In other words, it will send packets to its neighbors with a higher probability as it moves between hotspot locations. Fig. 3.3 illustrates a concrete example of a lunch break but it is also possible that this hotspot might be a library or a classroom building.

The condition for deciding if a state s of a node is idle is given by the equation below. The node will stay idle ($s = 1$) as long as the inequality stays true. If the inequality becomes false, the node changes its state to active and stays active as long as the inequality stays false.

$$s = \begin{cases} \mathit{active} & T_{\text{current}} - T_{\text{last}} > \mathit{timelimit} \\ \begin{cases} \mathit{idle} & \dfrac{T_{\text{last}} - T_{\text{prev}}}{T_{\text{current}} - T_{\text{last}}} > \beta \\ \mathit{active} & \text{otherwise} \end{cases} \end{cases}$$

The state deciding equation has a *timelimit* parameter in terms of seconds. The state decision function decides if the time difference between current encounter and last encounter is less than or equal to half of the time between previous encounter and last encounter. If this condition is true it means the encounter frequency is increased however if the time differences are big, the time differences may be showing wrong results. In order to prevent that we have added a *timelimit* check. If time between current encounter and last encounter is greater than *timelimit* parameter, it means time difference is not small enough to interpret that the node is in some crowded place. This *timelimit* shows the amount of time that a node encounters with other nodes frequent enough to be interpreted as "the node is in a crowded place". According to the campus environments properties (the percentage of undergraduate and graduate students, academic and technical staff) we used different values for *timelimit* parameter. Fig. 3.4 shows an example encountering times of a node to show a graphical explanation of working principle of state deciding equation.

If the node is in *active* state, its delivery probability increases as it encounters with other nodes. Pf (probability to forward) value quickly approaches to P_{wanted} as it encounters with other nodes. When a node encounters with another node, it opens a session with the other node with a probability Pf. Whether the node has opened the session with the other node or not, the node will update its Pf value.

If the node is in *idle* state, Pf decreases fast as the time passes but it will always be higher than 0. Unlike PROPHET [4], each node has one Pf value that applies for all the encountered nodes. In this situation, we suppose that the node is in a crowded waiting place. In that case we expect the node's encounter frequency with other nodes to increase. If the node leaves the waiting place then it will change its state to active again. In that case Pf value starts to be updated according to being in active state.

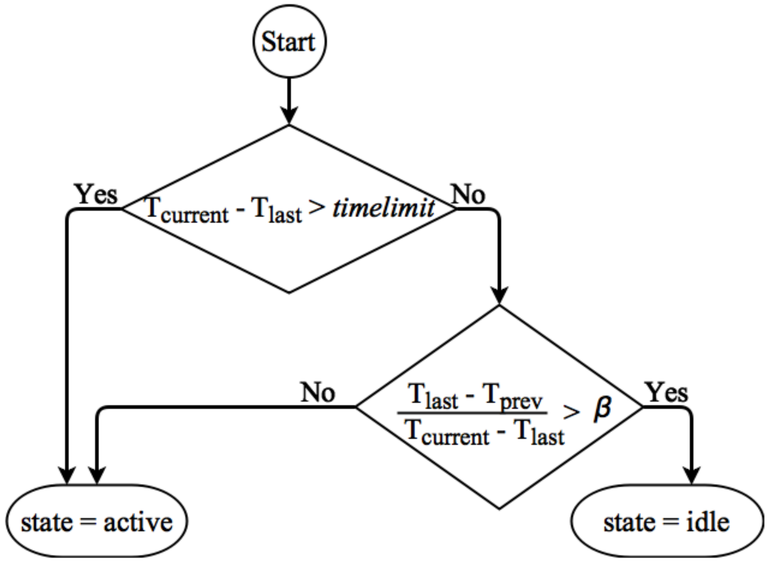

Figure 3.4: Flowchart of state decision

The probability to forward a message of an idle node is given as follows.

$$Pf_{\text{new}} = (\alpha^2 \times Pf_{\text{old}} + (1 - \alpha) \times P_{\text{wanted}}) \times \lambda \tag{3.1}$$

The probability to forward a message of an active node is given as follows.

$$Pf_{\text{new}} = \alpha^2 \times Pf_{\text{old}} + (1 - \alpha) \times P_{\text{wanted}} \tag{3.2}$$

Every node holds the last contact start time T_{last} and the one before last encounter T_{prev}. The current encounter time is denoted by T_{current}. When a node encounters with another node, inter-contact time differences are calculated to decide if the node is idle.

In the Equation 3.2, α is a constant aging parameter that we empirically set using the encounter datasets. P_{wanted} is also a constant parameter which defines the wanted probability value. Pf is expected to approach to P_{wanted}. The best possible P_{wanted} value is also found empirically for campus environments. The equation brings the Pf to P_{wanted} quickly because if a person is waiting in a hotspot (e.g., restaurant, class, library), then we expect him or her to stay there for a time period. Pf is not becoming 0 as we would like to use the possibility of sending message all the time while limiting the excessive message transmissions. Although we expect that the person mostly contacts with the same people, new nodes may arrive to the waiting place. In the SCR method, a node keeps only the last two encounter times in its buffer unlike methods such as PROPHET that holds all the delivery probabilities of the encountered nodes. For a network setting with thousands of nodes, SCR does not require the nodes to keep track of many delivery probability values in the buffers of the nodes. In addition, sending all the delivery probabilities of a node to the other nodes may bring an extra communication overhead. In other words, crowded environments can bring another overhead to the protocols such as PROPHET while this is not the case for SCR. Therefore, SCR can be considered as a lightweight routing protocol.

CHAPTER 4
SIMULATION STUDY

4.1 Dataset Description

We use three datasets in our simulation study. The datasets contain mobility traces collected from people at University of Milano [46], University of Cambridge [47] and University of St Andrews [48].

4.1.1 University of Milano Campus dataset

The Milano campus mobility data is taken from the CRAWDAD archive. Researchers have given Pocket Mobile Trace Recorders (PMTRs) to 49 people. Human walk traces were collected for 19 days in November 2008. The carriers of the devices were faculty members, doctoral students, and technical staff. The PMTR devices do not have Bluetooth but they have a 10 meter connectivity range which is similar to the Bluetooth transmission range. The data contains the encounter information between the nodes. Each encounter data contains the node IDs and start and end time of the connection. Total encounter data has 11895 entries. 5 users having no encounter data are filtered out, leaving us 44 users.

4.1.2 University of Cambridge Campus dataset

The mobility dataset contains 4228 entries that contains similar encounter information. The data contains 6 days of encounter data. Researchers have given iMote devices to 12 doctoral students at the System Research Group to keep track of their encounter data. These devices have Bluetooth connectivity with 10 meter contact range. The original dataset contains traces of 12 participants with any other Bluetooth enabled devices. On the other hand, they have information regarding to other encountered people (non-participants). Under this condition it is not possible to know if a non-participant has forwarded its packets to other nodes so we filtered out the data of the non-participants.

4.1.3 University of St Andrews

This encounter dataset contains encounter start and end times of 27 participants (22 undergraduate students, 3 graduate students and 2 staff) at University of St Andrews. The data contains 79 days of traces. The devices were T-mote devices that have a 10 meters contact range similar to Bluetooth transmission range. In their study case the T-mote devices recorded the contacts with other nodes and uploaded this data to base stations in the campus. We only used the node ids, encounter start time and encounter end time data and ignored all other data in this dataset. The original dataset had also Facebook friend connections data which we ignored for our study. After deleting the duplicate entries, we had an 55238 entry dataset.

4.2 Intercontact Times and Durations

From our datasets, we have extracted the Probability Distribution Functions of inter contact times and inter contact durations. Inter contact time is defined as the time between two successful contacts between two nodes. Inter contact duration is the duration of a contact between two nodes. Chaintreau et al. [49] defines inter contact time and inter contact duration as two important metrics that shows the capacity of the opportunistic network. Inter contact duration will give an idea about the data exchange rate at each encounter. Inter contact time will give an idea about total throughput in the network. We calculated inter contact times and inter contact durations to see how similar are the data or what are the properties of the data. These information may be helpful while interpreting the metric results of our model with other routing approaches.

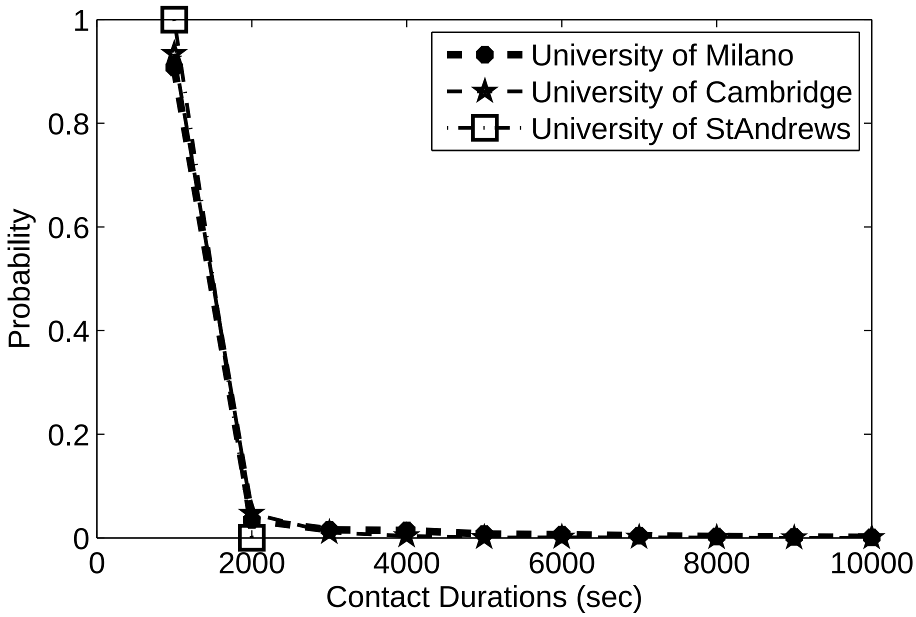

Figure 4.1: PDF of inter contact durations of datasets

Inter contact durations of University of Milano and University of Cambridge follows the same distribution nearly. University of St Andrews data seems to follow the same distribution with a difference. Maximum inter contact duration of University of St Andrews is about 2000 and follows a tight distribution whereas the other datasets follows a broad distribution. This may be because the majority of the participants of walk trace was undergraduate students in University of St Andrews. Undergraduate students may be encountering each other at lectures and leaving school when their day ends whereas faculty members and graduate students may be staying at their offices all day long together. Other datasets contain data of graduate students or a mixture of students and staff. As an overall view, their distribution behavior is similar. This shows that the datasets are consistent and represents university environment as expected.

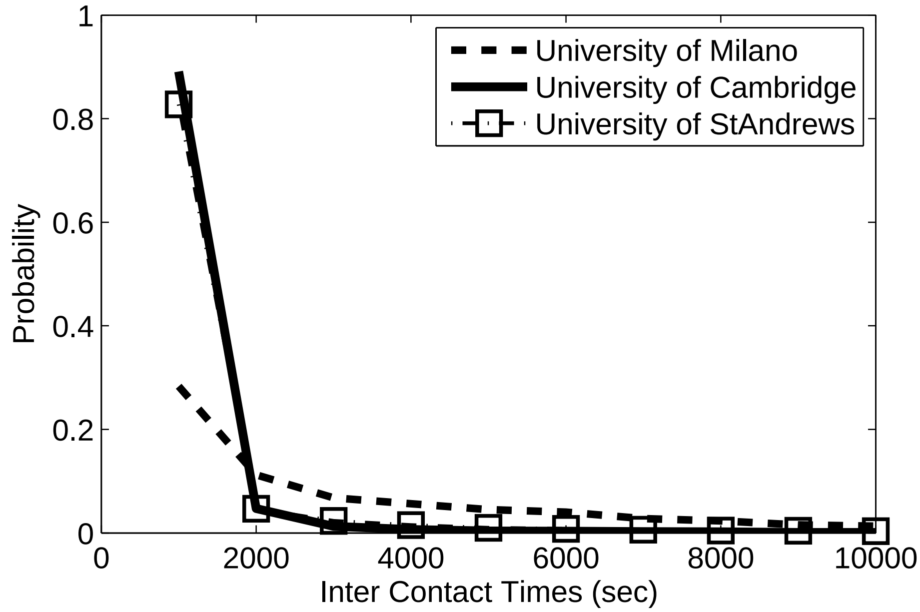

Figure 4.2: PDF of inter contact times of datasets

Inter contact times of University of Cambridge and University of St Andrews follow nearly the same distribution. After 2000 seconds the distributions are very similar. The University of Milano dataset shows a decrease till 2000 seconds but the slope is smaller comparing with other datasets. The University of Milano dataset has less number of short inter contact times (less than 2000 seconds) than other datasets. It means the people in University of Milano meet with each other less frequently than other datasets. The reason for this may be that University of Milano dataset contains wider range of participants than other datasets. University of St Andrews dataset contains mostly walk traces of undergraduate students whereas University of Cambridge dataset contains mostly walk traces of doctoral students. University of Milano dataset contains traces of faculty members, doctoral students and technical staff. Faculty members, technical staff and doctoral students population may be encountering each other less frequently than student populations. Another reason may be that students may be more mobile than any other people group in university campuses. As they are more mobile they have more chance of seeing each other on the campus. Technical staff and faculty members may be more stable and have less chance of seeing each other. As an overall view, the distribution behaviors of datasets are similar.

4.3 Metrics and Simulation Setup

We use three metrics in our simulation study: success rate (i.e., message delivery success ratio), message delay, and number of packets. *Success Rate* shows the distribution percentage of the messages. *Message Delay* shows the average delivery latency of the messages. *Number of packets sent* metric is the main identifier of the energy consumption of the mobile devices.

Let us briefly summarize the assumptions in our simulations. We assume that the encounter times between the nodes are sufficient for message exchanges. We assume that the messages in the network are text-based and with a limitation of 200 characters such as an SMS message. We have set the error rate of the transmissions as 10%. Error rates follow uniform distribution through the simulation. In our simulation study we assumed that the communication between two nodes are not interfered with other communication around. As the main communication protocol we assumed is Bluetooth this assumption is realistic. For instance, there is no acknowledgment requirement. Specific protocol related packets (e.g., TCP, UDP) for opening or closing a session are also not taken into account.

All the message delay data were shown in terms of seconds. We calculated the message delay as follows: For all copies of some specific message, we have calculated the difference between creation time of the first packet and creation time of the other packets. We got the sum of these differences and divided it with the number of nodes that received the packet. In this case the nodes that received the packet will be one less than the number of nodes that have the packet. This is because the first packet is created at the creator node makes it created message rather than received message. This metric can be biased if used alone. Given that there are two messages. One of them has been broadcasted to only one node with a very small delay whereas the other message has been broadcasted to many nodes with some delay. In this case the message that is broadcasted to only one node will have lower message delay then the one who is broadcasted to a wider number of nodes. As we get average while calculating this metric, it is possible that we may face with a biased result. To prevent that, the message delay should be considered together with the success rate. We have calculated success rate as follows: for all distinct messages, we calculated how many nodes have taken that specific message. For all distinct messages we found the ratio of number of copies of the message with specific id to number of all nodes.

We have developed a custom simulator for our routing strategy. Our simulator accepts the aforementioned trace-file content containing nodes and their contact start and end times in seconds. In each simulation run, 100 distinct messages are generated randomly by various nodes in the mobility trace data at uniformly distributed times. All the created messages have a 48 hour TTL (Time To Live) value which makes a packet expired after the creation time of the first copy of the message. Each result in the simulation study is based on 200 simulation runs for significance.

The outcomes of the proposed routing strategy is compared with epidemic, epidemic with TTS, PROPHET, NDAO and random routing strategies. The description of these routing strategies are explained below.

- *Epidemic* routing was proposed by Vahdat and Becker [6]. In this routing type every node sends the messages it has to other nodes whenever it encounters. Nodes exchange their message vectors to notify each other about the id of the packets that they do not have in their buffer.

- *Epidemic with TTS* is a routing scheme such that each node can only forward certain copies of a given message [50] according to the TTS value. Every time a node sends a copy of the message to the receiver node, the TTS of the message is decreased by one. The node cannot send more copies of a message if the TTS value of this message reaches to 0 or 48 hours of expiration time passes. We set the TTS value to 2 in epidemic with TTS.

- *Node density aware opportunistic routing (NDAO)* is proposed by Lu et al. [5]. In this routing strategy a node sends the message to its neighbor node if the number of neighbors of that node is less than some threshold value. The threshold is updated to current number of neighbor count of the node every time when that node encounters another node. This routing strategy requires each node to keep track of the number of neighbor nodes.

- *Random routing* is a variation of the epidemic routing. In random routing, for each encounter, every node sends the message with some predetermined and static probability. We compare SCR with random routing with probability to forward value of 10%.

- In *PROPHET* routing strategy, whenever an encounter happens, each node updates delivery predictability (i.e., delivery probability) between itself and its neighbor. P_{init} is set to 0.75, with $\gamma = 0.98$ and $\beta = 0.25$ as suggested in [4]. In PROPHET routing every node keeps track of the nodes that it encountered.

- For *SCR*, we empirically set the parameters of SCR α as 0.25 and P_{wanted} as 0.99. The best λ value producing the least amount of sent messages without having significant loss in success rates and increase in message delays is 0.99. β value is set to 2. For University of Cambridge and University of Milano *timelimit* value is set to 1350 whereas for University of St Andrews, it is set to 410. The parameters for simulation runs are shown in Table 4.1.

Table 4.1: Simulation Parameters for SCR

	University of Milano	University of Cambridge	University of St Andrews
α	0.25	0.25	0.25
P_{wanted}	0.99	0.99	0.99
λ	0.99	0.99	0.99
β	2	2	2
timelimit	1350	1350	410

4.4 Performance Results

We compared SCR with epidemic, PROPHET, epidemic with TTS and random routing in terms of success rates, message delays and number of packets sent. The success rate gives information about the routing strategy's success in terms of message propagation ratio. The success rate metric will give information about the message delivery success rate of the routing method in the network environment. In other words this metric is a representation of how much a routing method allows a message to propagate through the network. The message delay gives information about on average how fast a message can be delivered by the routing strategy. This metric plays an important role where the messages have a TTL value that makes the message expired and does not worth sending after expiration time. TTL valued message means the message contains some information that should be delivered before it expires or loses its importance. In this case the message delay metric will give the researcher information about the routing method delivery speed. As the main energy consuming operations in a mobile device is wireless communication, the number of packets sent metric will give an idea about the energy usage of the routing method.

4.4.1 Success Rates

4.4.1.1 CDF Graph Results

Let us first start our discussion of the experimental results with the cumulative distribution function (CDF) of success rates for the University of Milano and University of

Cambridge datasets. Although the size of the University of Cambridge dataset is smaller, it shows similar results with University of Milano. For the University of St Andrews dataset SCR gives a similar curve with epidemic, PROPHET and NDAO. Epidemic with TTS and random routing seems to have lower success rates. Success rates greater than 60% forms about 40% of the result data of SCR, epidemic, PROPHET and NDAO. Random routing has about 9% result data that has success rate greater than 60% and epidemic with TTS has about 25% result data.

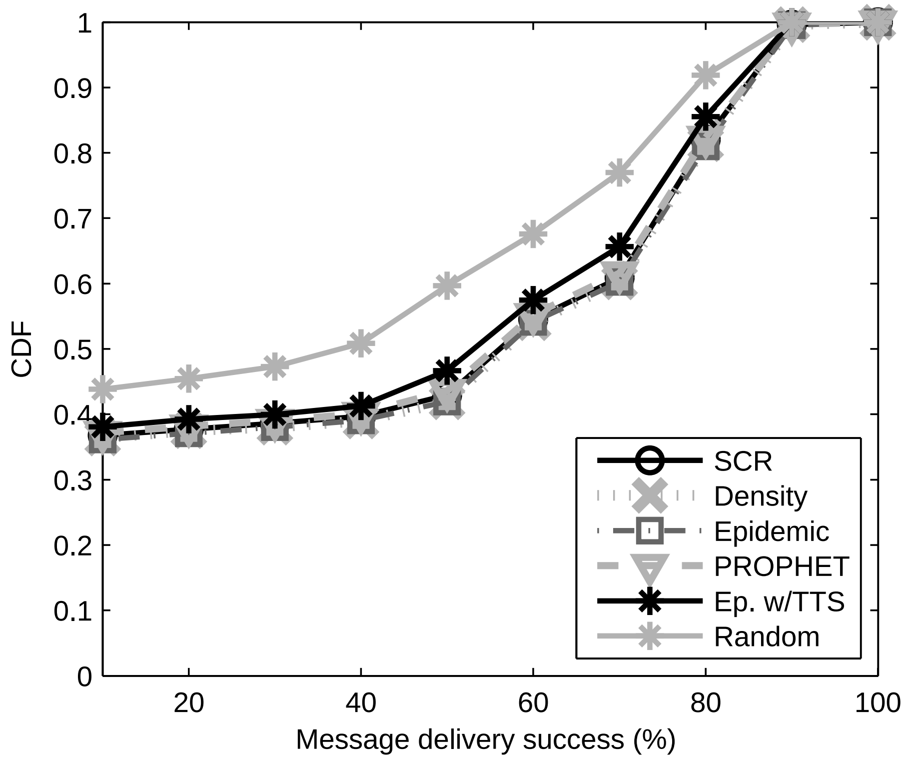

Figure 4.3: CDF of message delivery success for the University of Milano dataset.

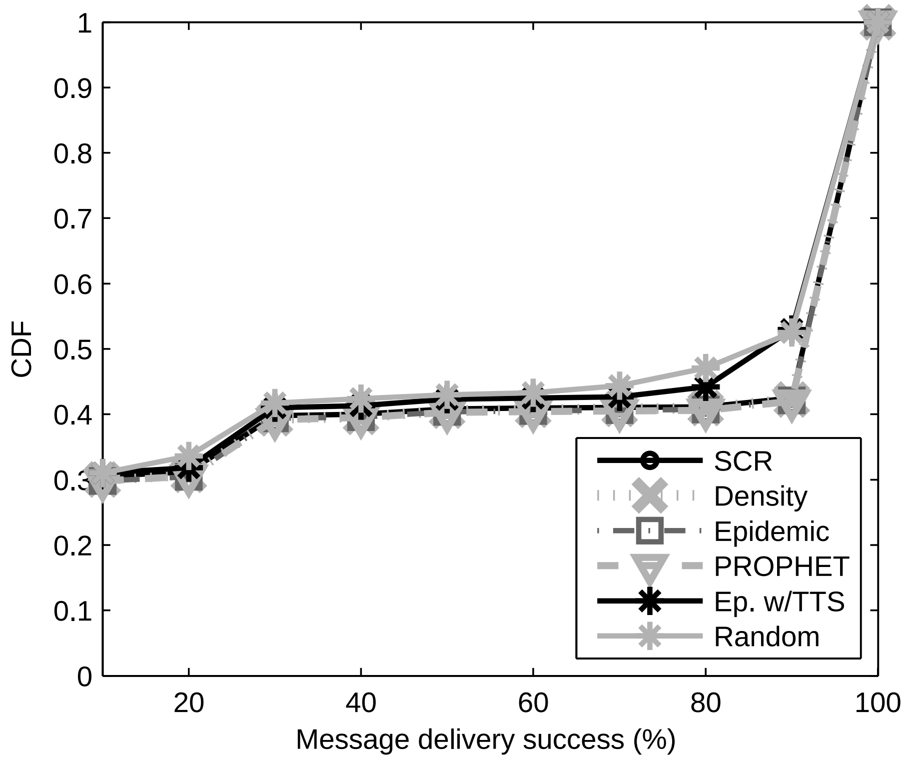

Figure 4.4: CDF of message delivery success for the University of Cambridge dataset.

The difference between epidemic with TTS and random routing becomes more clear as the dataset gets bigger. The University of St Andrews dataset is the largest whereas the University of Cambridge is the smallest dataset in our experiments. University of St Andrews and University of Milano figures curve more than University of Cambridge dataset. This may be because the duration of the trace collection time in University of Cambridge. The trace collection duration is not enough for routing strategies to show their full performance clearly. This may be the reason that the success rate graph of University of Cambridge dataset keeps increasing and does not show a curve.

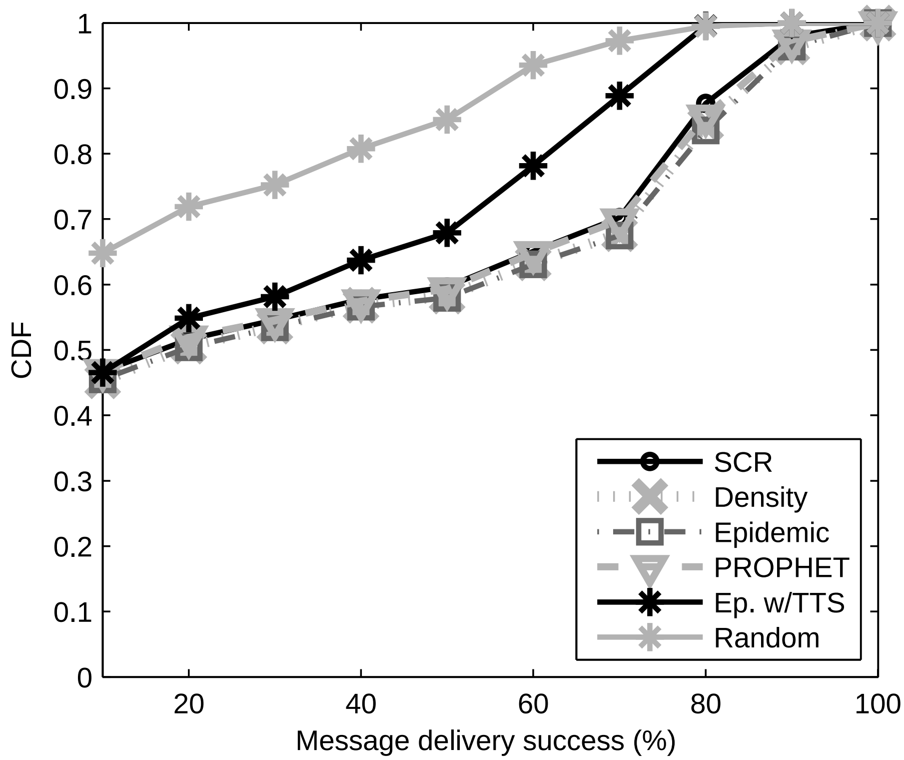

Figure 4.5: CDF of message delivery success for the University of St Andrews dataset.

4.4.1.2 Confidence Intervals

The boxplot of University of Milano is shown in Fig. 4.6. The distribution of routing types epidemic, PROPHET and SCR shows similar distributions with nearly the same success rates. NDAO shows success rates lower than SCR, epidemic and PROPHET. Epidemic with TTS and random routing shows low success rates.

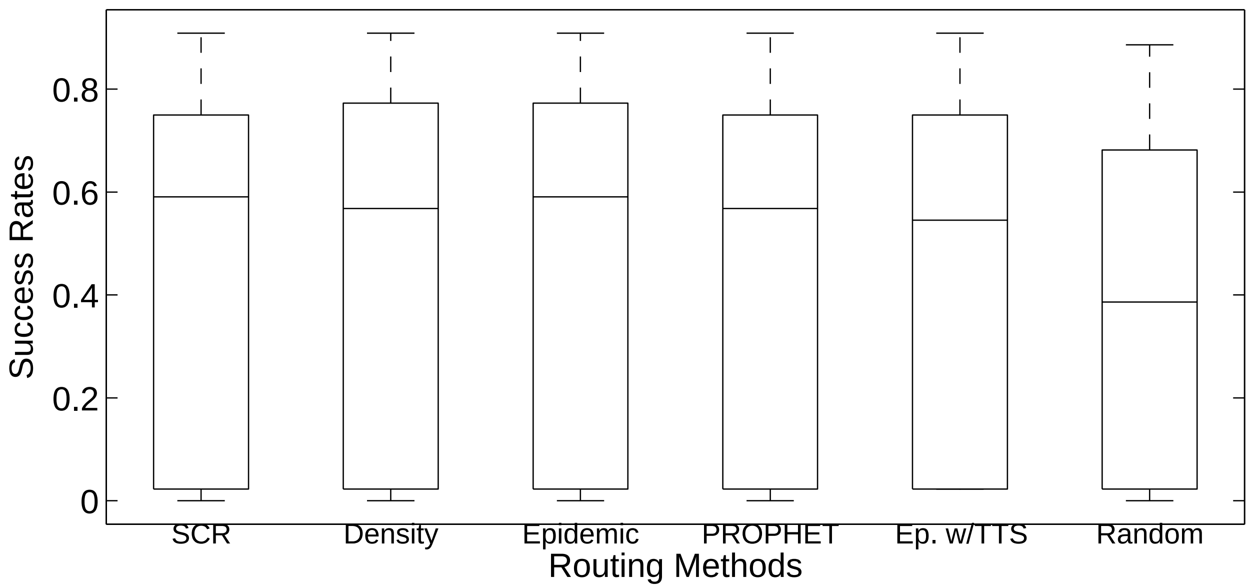

Figure 4.6: Message delivery success for the University of Milano dataset.

The boxplots of University of Cambridge is shown in Fig. 4.7. Epidemic, NDAO, PROPHET and SCR gives very similar message delay rates which are higher than random routing and epidemic with TTS. University of Cambridge dataset results do not show much difference between SCR, PROPHET,epidemic and NDAO probably because the trace dataset is small however it gives meaningful results that are consistent with results from other trace datasets.

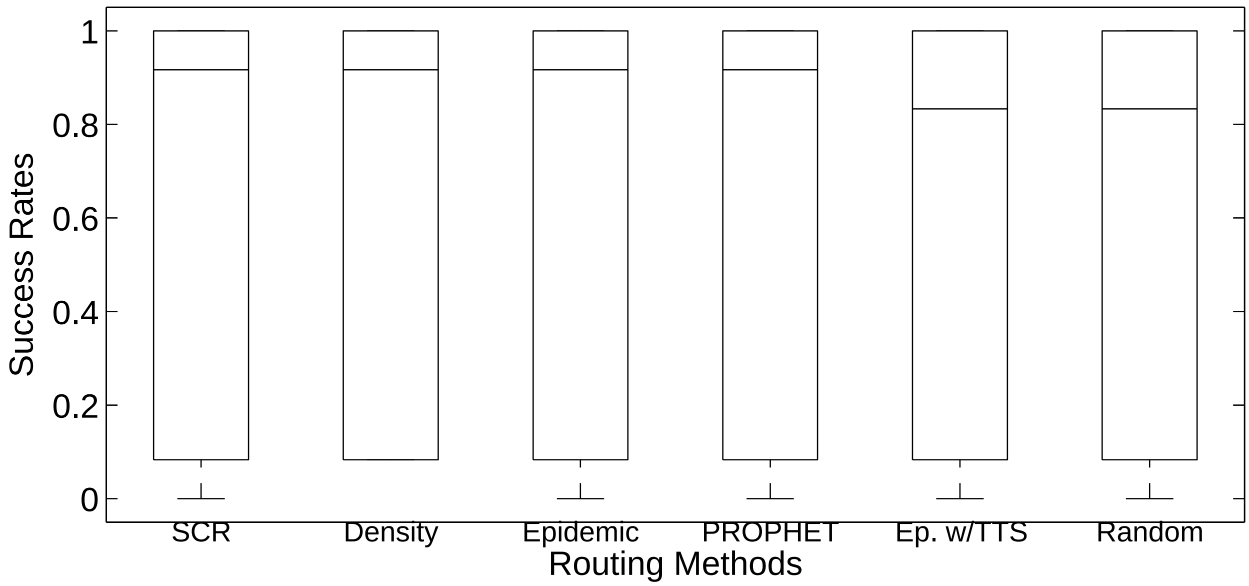

Figure 4.7: Message delivery success for the University of Cambridge dataset.

The boxplots of University of St Andrews is shown in Fig. 4.8. NDAO and epidemic shows similar success rates. Success rate of PROPHET is lower than NDAO and epidemic. SCR shows lower success rate than epidemic, NDAO and PROPHET. This may be because the trace dataset of University of St Andrews mostly contains traces of undergraduate students. It is possible the participants may be staying together longer than the participants of other walk traces (University of Cambridge and University of Milano). They may be going to classes or having time together after the classes.

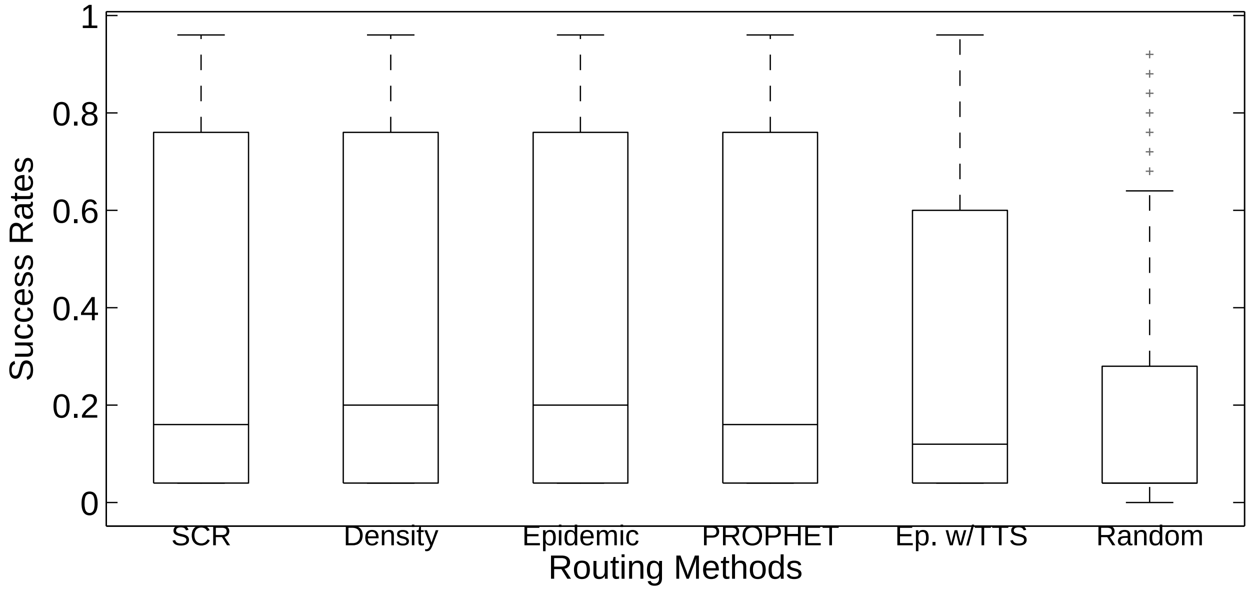

Figure 4.8: Message delivery success for the University of St Andrews dataset.

4.4.2 Message Delays

4.4.2.1 CDF Graph Results

We continue our discussion of the experimental results with the analysis of the message delay performances. Fig. 4.9 shows the CDF results of the routing protocols for the University of Milano dataset. The ratio of messages for smaller message delays is less for the random routing compared to the other four protocols. On the other hand, all the other protocols provide a better performance in terms of the message delays. Delays more than 85000 seconds (about 24 hours) form about 40% of the result data of random routing whereas about 32% of the other routing protocols.

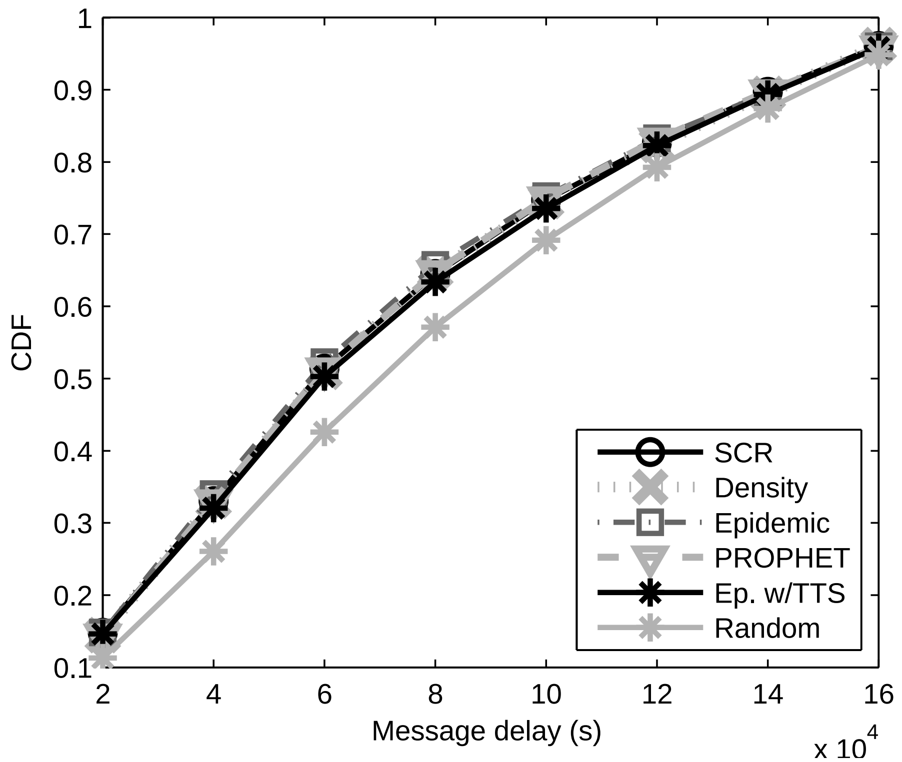

Figure 4.9: CDF of message delays for the University of Milano dataset.

We analyze the message delays for the University of Cambridge dataset in Fig. 4.10. As it can be seen in this figure, epidemic, epidemic with TTS and PROPHET show similar message delays. NDAO shows more message delay than other routing types unlike the case in University of Milano. Delays more than 85000 seconds (about 24 hours) forms about 14% of the result data of random routing whereas about 12% of the NDAO. Other routing types including SCR have delays of more than 85000 seconds about 9%.

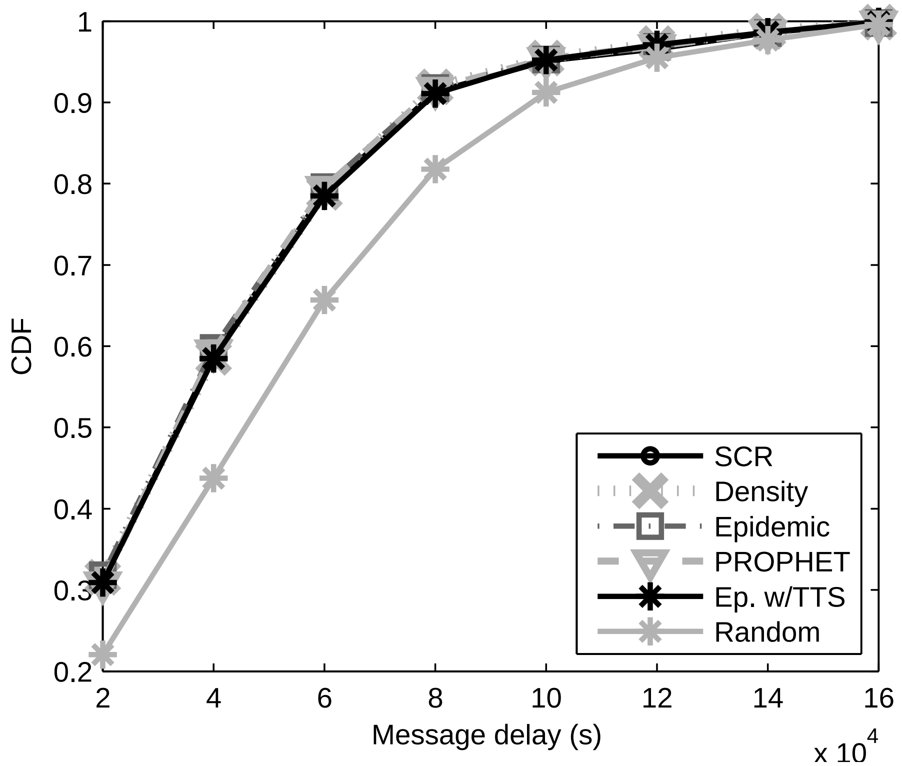

Figure 4.10: CDF of message delays for the University of Cambridge dataset.

We analyze the message delays for the University of St Andrews dataset in Fig. 4.11. All routing types except random routing show similar message delays. The difference between random routing and other routing types can be seen clearly in the graph of this dataset. Delays of more than 85000 seconds (about 24 hours) form about 45% of the result data of random routing whereas about 20% of the other routing types.

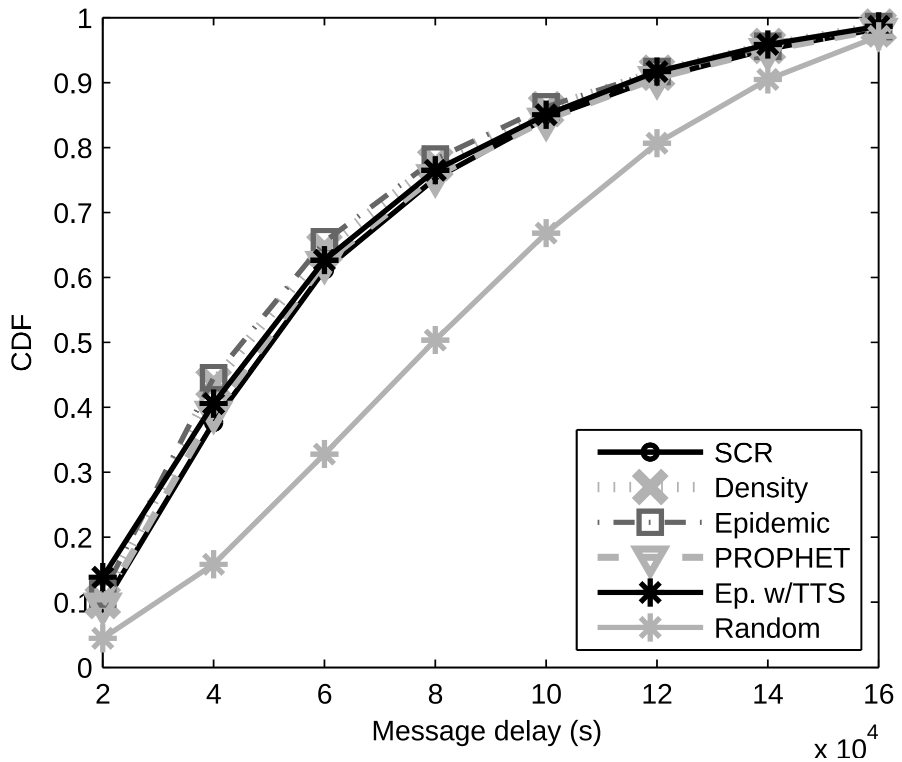

Figure 4.11: CDF of message delays for the University of St Andrews dataset.

4.4.2.2 Confidence Intervals

The boxplots of University of Milano are shown in Fig. 4.12. The boxplots of University of Cambridge are shown in Fig. 4.13. The distribution of routing types except random routing show similar results for both dataset results. The medians of SCR, NDAO, epidemic and PROPHET points similar results also. Random routing has more message delay and its distribution is wider as it is based on chance more. These graphs are consistent with CDF results of message delays.

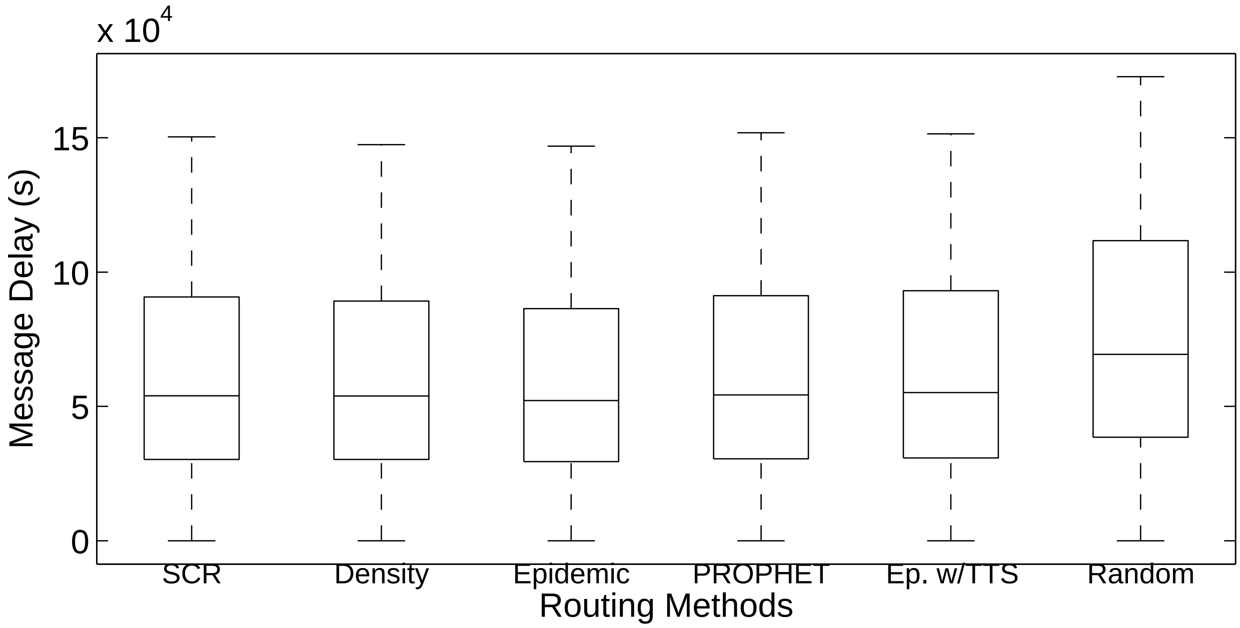

Figure 4.12: Message delays for the University of Milano dataset.

The boxplots of University of Cambridge is shown in Fig. 4.13. All routing models except random routing show nearly the same median values for message delays and similar distributions for University of Cambridge dataset. This dataset was smaller than the other two data datasets. It is possible that the trace collection duration was not sufficient to see a difference between the routing methods clearly in this dataset.

The boxplots of University of St Andrews is shown in Fig. 4.13. Routing models except random routing shows similar results for message delays. SCR shows higher message delay than NDAO and epidemic but the difference is very small. SCR shows very similar results with PROPHET. Random routing shows wider distribution than others. It also has a higher median value for message delay.

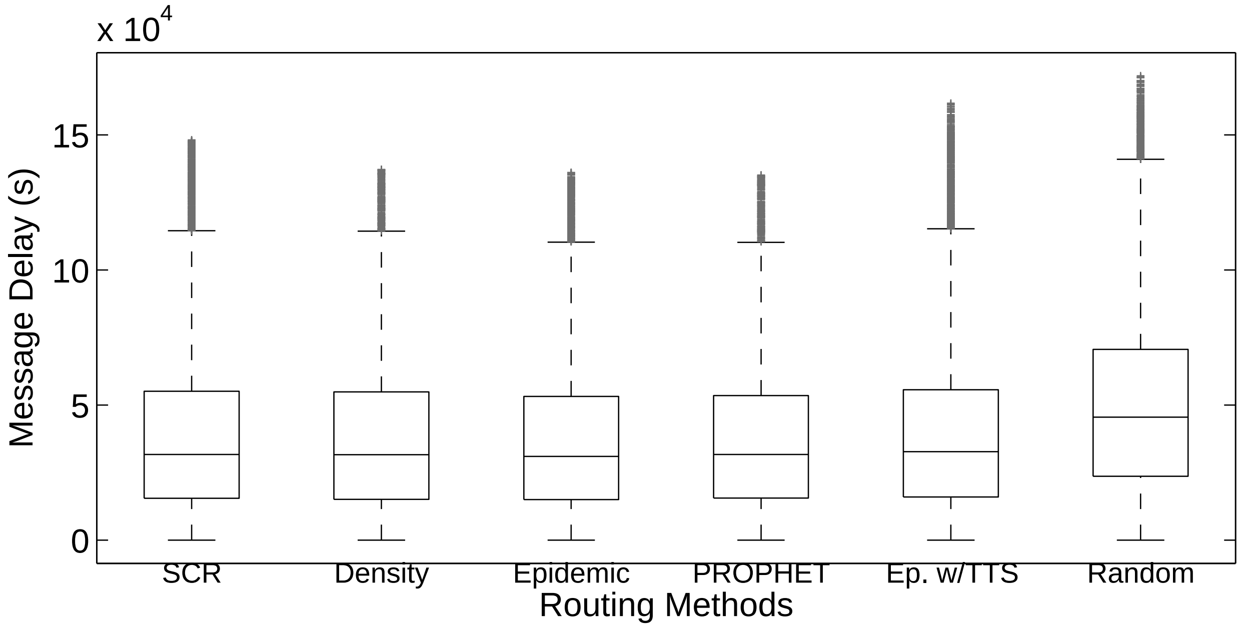

Figure 4.13: Message delays for the University of Cambridge dataset.

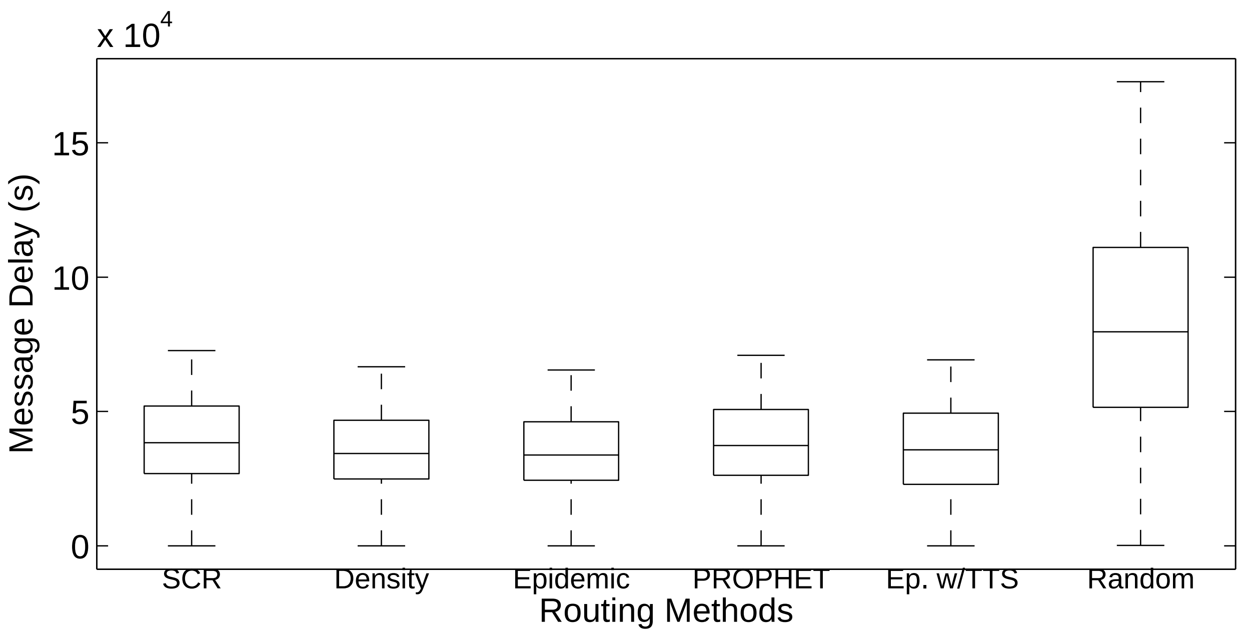

Figure 4.14: Message delays for the University of St Andrews dataset.

4.4.3 Number of Transmitted Packets

Lastly, we analyze the number of packets that are transmitted between the nodes of the network. This metric shows the success of SCR routing comparing with other routing methods. Average number of transmitted packets acquired from the experiment results are given in the bar charts. Each bar in the bar charts also shows the standard deviation of the results as an error line. According to the results of the bar charts, SCR sent the least amount of packets among the compared routing models. SCR sent about 10% to 20% less packets than epidemic and about 5% to 10% less than NDAO.

Fig. 4.15 shows the results for the University of Milano dataset. Despite having similar message delay and success rate performances, we find that SCR has sent significantly less (about 20%) amount of packets than the epidemic routing and about 10% less than PROPHET.

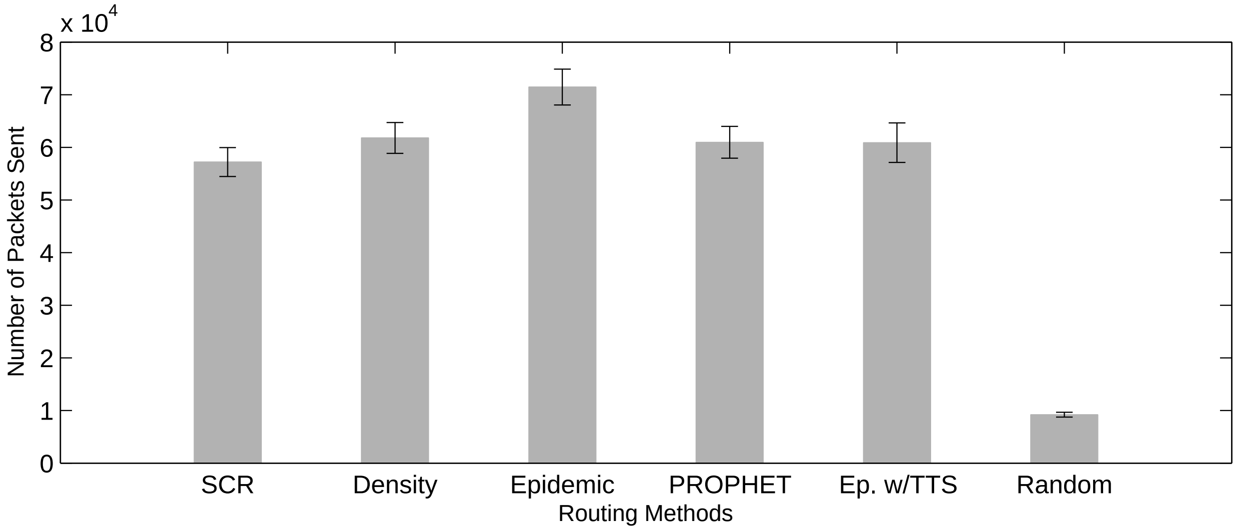

Figure 4.15: Number of transmitted packets for the University of Milano dataset.

For the University of Cambridge dataset, as shown in Fig. 4.16, SCR has sent about 20% less packets than the epidemic routing and 15% less than PROPHET. For the University of St Andrews data, as shown in Fig. 4.17, SCR again seems to send less packets than Epidemic, PROPHET and NDAO. SCR sent nearly 20% less number of packets than epidemic and NDAO. PROPHET also seems to sent less number of packets than Epidemic and NDAO however it does not seem as efficient as SCR. As expected, epidemic has the worst performance due to the fact that data is forwarded in every encounter without any limitation. Random routing sent the least amount of packets for both datasets however the results for message delays and success rates were worse.

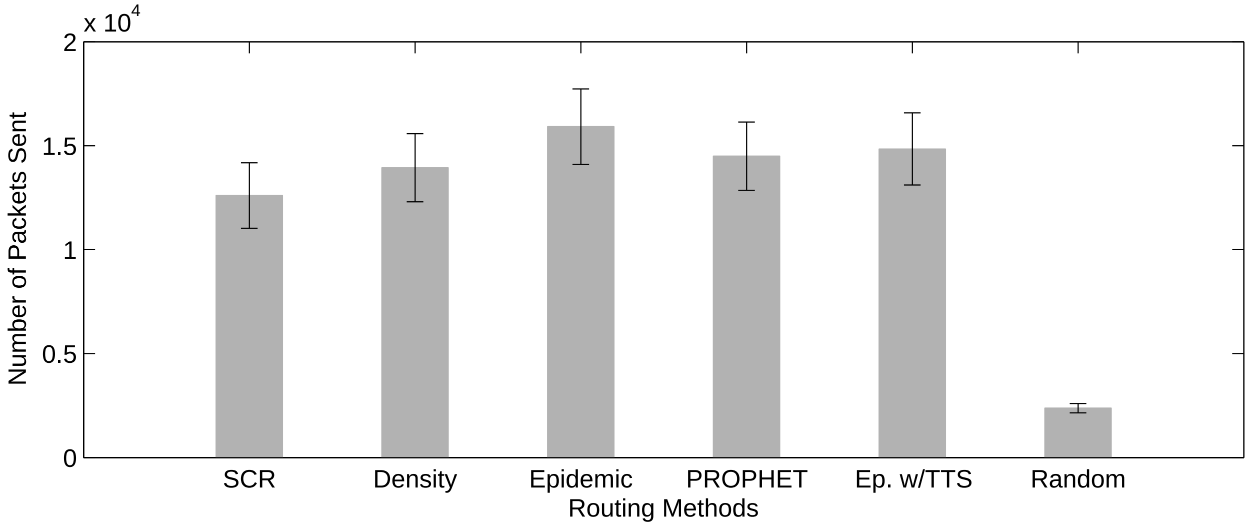

Figure 4.16: Number of transmitted packets for the University of Cambridge dataset.

The number of packets sent in the simulations for University of Milano is higher than the ones for University of Cambridge. This is an expected result since the Milano dataset was about 3 times larger than the other. This ratio can also be seen in both Fig. 4.15 and Fig. 4.16. The ratio of the standard deviations for the number of transmissions decreases as the dataset gets larger. In that sense, the use of the University of Milano dataset provides more satisfying and consistent results.

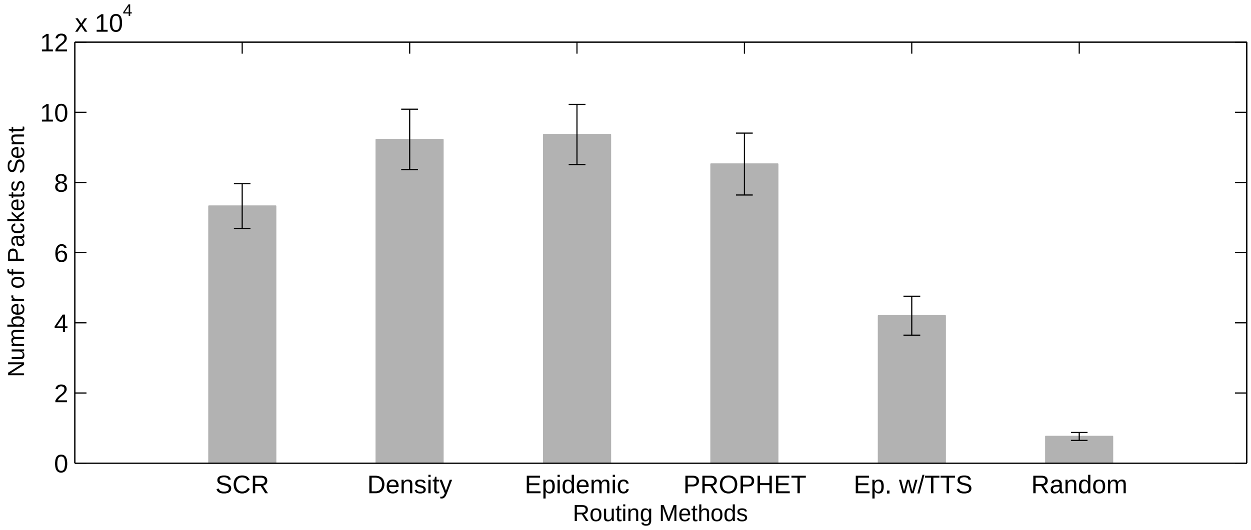

Figure 4.17: Number of transmitted packets for the University of St Andrews dataset.

For all the datasets SCR sent about 20% less number of packets than epidemic. For the University of Milano and University of Cambridge SCR sent about 10% less number of packets than NDAO whereas this ratio becomes about 20% in the University of St Andrews dataset. The reason of NDAO's that energy performance may be that undergraduate students may be staying connected together more than graduate students and staff. We can deduce that as the strategy for sending packet for a node in NDAO mainly depends on the stability of the number of the neighbors. Inter-contact durations of University of St Andrews supported this hypothesis by showing the contact durations lower than other datasets. Inter-contact durations of students at University of St Andrews are mostly less than 35 minutes which is approximately a lecture hour.

CHAPTER 5
CONCLUSIONS

In this thesis, we proposed an opportunistic networking strategy for campus environments. Our application scenario covered a message broadcasting system in a university campus via wireless transmission between mobile devices. Messages are broadcasted using flooding manner. We proposed the SCR protocol for efficiency in terms of number of transmissions, message delays and the delivery success rates.

To evaluate our proposed approach, we used datasets of various universities' campus human mobility walk traces. The datasets involve different densities of people types (i.e. undergraduate students, graduate students, faculty members, technical staff) on the campus. One of them was involving more graduate students, whereas the other one contains staff and technical person encounter data. Simulating with different types of data, our model showed successful results comparing with other routing methods. We compared the performance of SCR, NDAO, epidemic, PROPHET, epidemic with TTS and random routing methods. SCR sends about 10 to 20% less packets than epidemic and 5 to 10% less packets than NDAO routing. For the success rates and message delays SCR seems to give nearly the same performance with epidemic,PROPHET and NDAO in University of Milano and University of Cambridge dataset. The success rate and message delay performance of SCR comparing with NDAO and epidemic routing in University of St Andrews is quite close. We believe that our system can be used by universities as an emergency information system, yellow pages application or event announcement system.

LIST OF REFERENCES

[1] E. Nordström, P. Gunningberg, and C. Rohner, "Haggle: Relevance-aware content sharing for mobile devices using search @ONLINE."

[2] H. Ntareme, M. Zennaro, and B. Pehrson, "Delay tolerant network on smartphones: Applications for communication challenged areas," in *Proc. of the 3rd Extreme Conference on Communication: The Amazon Expedition (ExtremeCom'11)*, pp. 1–6, 2011.

[3] A. Triviño-Cabrera and S. Cañadas-Hurtado, "Survey on opportunistic routing in multihop wireless networks," *International Journal of Communication Networks and Information Security (IJCNIS)*, vol. 3, pp. 170–176, August 2011.

[4] A. Lindgren, A. Doria, and O. Schelen, "Probabilistic routing in intermittently connected networks," *ACM SIGMOBILE Mobile Computing and Communications Review*, vol. 7, no. 3, pp. 19–20, 2003.

[5] X. Lu, P. Lio, P. Hui, and Z. Qu, "Nodes density adaptive opportunistic forwarding protocol for intermittently connected networks," in *Identification, Information and Knowledge in the Internet of Things (IIKI), 2014 International Conference on*, pp. 297–300, Oct 2014.

[6] A. Vahdat and D. Becker, "Epidemic routing for partially connected ad hoc networks," tech. rep., Technical Report CS-200006, Duke University, 2000.

[7] T. Camp, J. Boleng, and V. Davies, "A survey of mobility models for ad hoc network research," *Wireless Communications and Mobile Computing*, vol. 2, no. 5, pp. 483–502, 2002.

[8] C. Hsu, M. Kuo, S. Wang, and C. Chou, "Joint design of asynchronous sleep-wake scheduling and opportunistic routing in wireless sensor networks," *IEEE Transactions on Computers*, vol. 63, pp. 1840–1846, July 2014.

[9] S. Misra, S. Pal, and B. K. Saha, "Distributed information-based cooperative strategy adaptationin opportunistic mobile networks," *IEEE Transactions on Parallel and Distributed Systems*, vol. 26, pp. 724–737, March 2015.

[10] W. Moreira, P. Mendes, and S. Sargento, "Opportunistic routing based on daily routines," in *Proc. of IEEE International Symposium on a World of Wireless, Mobile and Multimedia Networks (WoWMoM)*, pp. 1–6, June 2012.

[11] L.Song and D. Kotz, "Evaluating opportunistic routing protocols with large realistic contact traces," in *Proc. of the ACM MobiCom workshop on Challenged Networks (CHANTS)*, pp. 35–42, September 2007.

[12] J. Su, A. Goel, and E. Lara, "An empirical evaluation of the student-net delay tolerant networks," in *Proc. of the International Conference on Mobile and Ubiquitous Systems: Networks and Services (MOBIQUITOUS)*, July 2006.

[13] L. Vu, Q. Do, and K. Nahrstedt, "3R: Fine-grained encounter-based routing in delay tolerant networks," in *Proc. of WoWMoM*, pp. 1–6, June 2011.

[14] F. D. Rango, A. Socievole, and S. Marano, "Exploiting online and offline activity-based metrics for opportunistic forwarding," *Wireless Networks*, vol. 21, no. 4, pp. 1163–1179, 2015.

[15] A. Mtibaa, M. May, M. Ammar, and C. Diot, "PeopleRank: Social opportunistic forwarding," in *Proc. of IEEE INFOCOM*, pp. 1–5, March 2010.

[16] X. Mao, S. Tang, X. Xu, X. Li, and H. Ma, "Energy-efficient opportunistic routing in wireless sensor networks," *Parallel and Distributed Systems, IEEE Transactions on*, vol. 22, pp. 1934–1942, Nov 2011.

[17] R. Rohankar, "Agent based predictive data collection in opportunistic wireless sensor network," *Procedia Computer Science*, vol. 57, pp. 33 – 40, 2015. 3rd International Conference on Recent Trends in Computing 2015 (ICRTC-2015).

[18] M. S. Karyakarte, A. S. Tavildar, and R. Khanna *Wireless Personal Communications*, vol. 84, no. 1, pp. 729–744, 2015.

[19] M. C.-C. Hung, K. C.-J. Lin, C.-F. Chou, and C.-C. Hsu, "Effort: Energy-efficient opportunistic routing technology in wireless sensor networks," *Wireless Communications and Mobile Computing*, vol. 13, no. 8, pp. 760–773, 2013.

[20] S. Guo, L. He, Y. Gu, B. Jiang, and T. He, "Opportunistic flooding in low-duty-cycle wireless sensor networks with unreliable links," *IEEE Transactions on Computers*, vol. 63, pp. 2787–2802, Nov 2014.

[21] J. Chen, W. Zhang, and P. Giaccone, "Performance evaluation of routing protocols in opportunistic networks," in *Computing, Communication and Networking Technologies (ICCCNT), 2014 International Conference on*, pp. 1–7, July 2014.

[22] A.-K. Pietilainen and C. Diot, "CRAWDAD dataset thlab/sigcomm2009 (v. 2012-07-15)." Downloaded from http://crawdad.org/thlab/sigcomm2009/20120715, July 2012.

[23] A. J. Aviv, M. Blaze, M. Sherr, and J. M. Smith, "Privacy-aware message exchanges for humanets," *Computer Communications*, vol. 48, pp. 30 – 43, 2014.

[24] V. Srinivasan, M. Motani, and W. T. Ooi, "Analysis and implications of student contact patterns derived from campus schedules," in *Proc. of MobiCom*, pp. 86–97, 2006.

[25] Z. Feng and K. Chin, "On the performance of epidemic based routing protocols for delivering multicast bundles in delay tolerant networks," *International Journal of Wireless Information Networks*, vol. 21, no. 2, pp. 133–153, 2014.

[26] C. Liu and J. Wu, "On multicopy opportunistic forwarding protocols in nondeterministic delay tolerant networks," *Parallel and Distributed Systems, IEEE Transactions on*, vol. 23, pp. 1121–1128, June 2012.

[27] M. Xiao, J. Wu, and L. Huang, "Community-aware opportunistic routing in mobile social networks," *IEEE Transactions on Computers*, vol. 63, pp. 1682–1695, July 2014.

[28] K. Chen and H. Shen, "Maximizing p2p file access availability in mobile ad hoc networks though replication for efficient file sharing," *IEEE Transactions on Computers*, vol. 64, pp. 1029–1042, April 2015.

[29] W. Gao, Q. Li, and G. Cao, "Forwarding redundancy in opportunistic mobile networks: Investigation, elimination and exploitation," *IEEE Transactions on Mobile Computing*, vol. 14, pp. 714–727, April 2015.

[30] B. Han, J. Li, and A. Srinivasan, "On the energy efficiency of device discovery in mobile opportunistic networks: A systematic approach," *IEEE Transactions on Mobile Computing*, vol. 14, pp. 786–799, April 2015.

[31] P. Vieira, A. Costa, and J. Macedo, "A comparison of opportunistic connection datasets," in *Emerging Intelligent Data and Web Technologies (EIDWT), 2012 Third International Conference on*, pp. 66–73, Sept 2012.

[32] X. Hu, T. Chu, V. Leung, E.-H. Ngai, P. Kruchten, and H. Chan, "A survey on mobile social networks: Applications, platforms, system architectures, and future research directions," *IEEE Communications Surveys and Tutorials*, vol. PP, no. 99, pp. 1–1, 2014.

[33] M. Papadopouli and H. Schulzrinne, "Effects of power conservation, wireless coverage and cooperation on data dissemination among mobile devices," in *Proc. of the 2Nd ACM International Symposium on Mobile Ad Hoc Networking & Computing*, MobiHoc '01, pp. 117–127, 2001.

[34] A. Lindgren, A. Doria, J. Lindblom, and M. Ek, "Networking in the land of northern lights: Two years of experiences from dtn system deployments," in *Proc. of the 2008 ACM Workshop on Wireless Networks and Systems for Developing Regions*, WiNS-DR '08, pp. 1–8, 2008.

[35] G. Solmaz, K. Akkaya, and D. Turgut, "Communication-constrained p-center problem for event coverage in theme parks," in *Proceedings of IEEE GC'14*, pp. 486–491, December 2014.

[36] G. Solmaz and D. Turgut, "Event coverage in theme parks using wireless sensor networks with mobile sinks," in *Proceedings of IEEE ICC'13*, pp. 1522–1526, June 2013.

[37] G. Solmaz and D. Turgut, "Optimizing event coverage in theme parks," *Wireless Networks (WINET) Journal*, vol. 20, pp. 1445–1459, August 2014.

[38] G. Solmaz and D. Turgut, "Tracking evacuation of pedestrians during disasters," in *Accepted to appear in IEEE GLOBECOM'15*, December 2015.

[39] P. Juang, H. Oki, Y. Wang, M. Martonosi, L. Peh, and D. Rubenstein, "Energy-efficient computing forwildlife tracking: Design tradeoffs and early experiences with zebranet," in *The Tenth International Conference on Architectural Support for Programming Languages and Operating Systems*, 2002.

[40] N. Glance, D. Snowdon, and J.-L. Meunier, "Pollen: using people as a communication medium," *Computer Networks*, vol. 35, pp. 429–442, March 2001.

[41] A. Pentland, R. Fletcher, and A. Hasson, "Daknet: rethinking connectivity in developing nations," *Computer*, vol. 37, pp. 78–83, Jan 2004.

[42] M. Conti, F. Delmastro, and A. Passarella, "Context-aware file sharing for opportunistic networks," in *Int. Conf. on Mobile Adhoc and Sensor Systems*, pp. 1–3, Oct 2007.

[43] Y. Mahéo, N. L. Sommer, P. Launay, F. Guidec, and M. Dragone, "Beyond opportunistic networking protocols: a disruption-tolerant application suite for disconnected manets," in *Fourth Extreme Conference on Communication (ExtremeCom'12)*, March 2012.

[44] V. Vukadinovic, F. Dreier, and S. Mangold, "A simple framework to simulate the mobility and activity of theme park visitors," in *Winter Simulation Conference (WSC) 2011*, pp. 3248–3260, December 2011.

[45] G. Solmaz and D. Turgut, "Theme park mobility in disaster scenarios," in *Proceedings of IEEE GLOBECOM'13*, pp. 377–382, December 2013.

[46] P. Meroni, S. Gaito, E. Pagani, and G. P. Rossi, "CRAWDAD data set unimi/pmtr (v. 2008-12-01)." Downloaded from http://crawdad.org/unimi/pmtr/, Dec 2008.

[47] J. Scott, R. Gass, J. Crowcroft, P. Hui, C. Diot, and A. Chaintreau, "CRAWDAD data set cambridge/haggle (v. 2006-01-31)." Downloaded from http://crawdad.org/cambridge/haggle/, Jan 2006.

[48] G. Bigwood, D. Rehunathan, M. Bateman, and S. Bhatti, "CRAWDAD data set st_andrews/sassy (v. 2011-06-03)." Downloaded from http://crawdad.org/st_andrews/sassy/, Jun 2011.

[49] A. Chaintreau, P. Hui, J. Crowcroft, C. Diot, R. Gass, and J. Scott, "Pocket switched networks: Real-world mobility and its consequences for opportunistic forwarding," tech. rep., August 2005.

[50] J. Tower and T. Little, "A proposed scheme for epidemic routing with active curing for opportunistic networks," in *Proc. of 22nd International Conference on Advanced Information Networking and Applications Workshops*, pp. 1696–1701, March 2008.