Opportunistic Message Broadcasting in Campus Environments

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***Abstract*—In this paper, 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' smart-phones 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 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 places. The proposed model is analyzed through extensive network simulations using mobility datasets collected from students on University of Milano and University of Cambridge campuses. The opportunistic network model and the SCR protocol are compared with epidemic, epidemic with TTS (Times To Send), PROPHET, and random routing protocols. The message delivery performance of SCR is close to Epidemic and PROPHET while SCR reduces the amount of message transmissions.**

I. Introduction

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 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 that 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 routes to the destinations because of the dynamic structure of the network. The second characteristic is that the traditional routing approaches 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 [1].

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 [2]. However, due to the fact that mobility of the nodes drastically change [3] 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.

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 such as dLife [4] require previous encounter information of the nodes in the network. Our method differs from these models in the sense that our routing strategy does not require prior knowledge about the system. This allows the network to maintain similar performances under various conditions such as newly added nodes or frequency changes of message generations in the system.

Our application scenario that we describe in Section III is based on broadcasting messages 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 happen 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 smart-phones of the students are used for hop-by-hop wireless transmissions. Each message has an expiration date according to the type of event.

We propose a routing protocol to work efficiently in the campus environments in Section IV. In our *state-based campus routing* (SCR) approach, the nodes change their generation of message delivery probabilities according to their states. The nodes can be either in idle or active state during their lifetimes. The current states of the nodes are based on the regions that the nodes are located such as hot-spots or deserted regions. The efficiency of the proposed network model and the SCR strategy is compared with epidemic, epidemic with TTS(Times To Send), PROPHET, and random routing protocols using mobility datasets from University of Milano and University of Cambridge in Section V. SCR provides close to Epidemic and PROPHET in terms of the delivery success rates and message delays, while it significantly reduces the message transmission counts.

II. Related Work

Let us briefly summarize the related literature on opportunistic routing strategies. Vahdat and Becker [2] 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 that are 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 that is proposed by Lindgren et al. [5] is an example of such routing strategies. SCR does not require this type of data exchange as they bring energy overhead and excessive message traffic.

Su et al. [6] provide Link State opportunistic routing strategy that is experimented using campus data. Link State routing strategy requires nodes to exchange their link state weights with each other besides their messages. Mtibaa et al. [7] propose PeopleRank routing where nodes send each other their PeopleRank values and social graph neighbors in each encounter besides their messages. 3R routing [8] 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 Katz [9] 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. [10] study epidemic routing on synthetically generated campus mobility data based on students' lecture schedules. Solmaz and Turgut [11] study the use of ad hoc networks in theme parks for event coverage, where they use mobile sinks for gathering messages from sensor nodes. Rahmatizadeh et al. [12] study routing towards a mobile sink using virtual coordinates.

Feng and Chin [13] experiment different variations of the epidemic routing in campus environments. Moreira et al. [4] 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. Lu et al. [14] 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.

III. Model Description

A. Campus environments

The campus environments are places where most actions happen according to daily routines. Daily activities of students

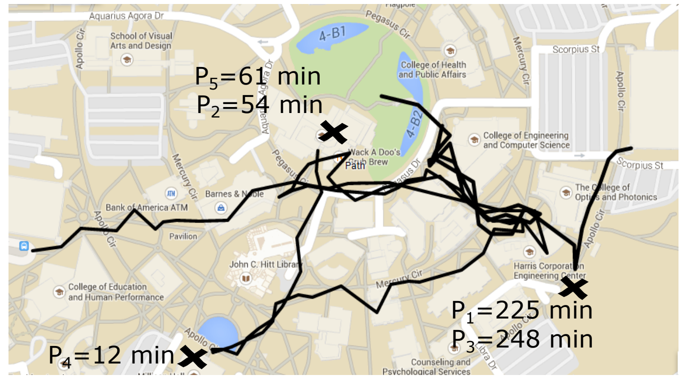

Fig. 1. A daily walk trace of a student in the UCF campus

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.

We collected 18 daily mobility traces using GPS-enabled smart-phones and observed the daily mobility patterns of the students from our research group. An example daily walk traces in the University of Central Florida (UCF) campus can be seen in Fig. 1. This figure shows the waiting times in 5 pause locations near the trajectory lines. 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. Lastly, we observe that most of the day is usually spent in indoor places and in only few locations where people gather such as the food court.

B. Opportunistic network model

We consider an opportunistic social network using the smart-phones of the students. In our application scenario, the messages are created by mobile nodes in university campus when an *event* occurs. The events occur in 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. The creator of the messages can be located in the departmental buildings or they can be security personnel patrolling in the campus.

A smart-phone 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 smart-phones 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 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.

IV. State-based Campus Routing (SCR) Protocol

We propose an opportunistic routing protocol based on the campus environments, which we name *state-based campus*

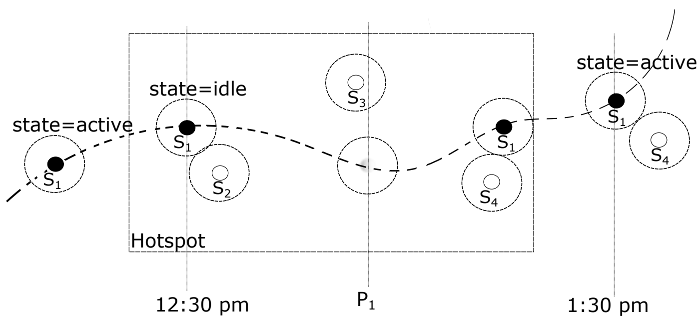

Fig. 2. A mobile node entering into a hotspot, waiting at pause point P_1, and leaving the hotspot.

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 encounter with nearly the same 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 [2]. 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 IDs 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. 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 comparing with its past encounter frequencies, then we suppose that the node is in a waiting place or in a *hot-spot*. 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.

Fig. 2 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. Node's probability to forward packets increase 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. 2 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.

$$s = \begin{cases} 1 & \dfrac{T_{\text{last}} - T_{\text{prev}}}{T_{\text{current}} - T_{\text{last}}} > 2 \\ & \\ 0 & \text{otherwise} \end{cases}$$

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 while it does not become 0 at any time. Unlike PROPHET [5], 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.

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

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

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

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

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

In the Equation 2, α is a constant ageing parameter which we empirically set the best value 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} in a fast way. This is because if a person is waiting in a hot-spot (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.

V. Simulation Study

A. Data Description

We use two datasets in our simulation study. The datasets contains mobility traces collected from people at University of Milano and University of Cambridge.

1) University of Milano Campus dataset: [15] Milano campus mobility data is taken from the CRAWDAD archive. Researchers have given Pocket Mobile Trace Recorders (PMTRs) to 49 people. The carriers of the devices were faculty members, doctoral students, and technical staff. The PMTR devices do not have Bluetooth connection but they have 10 meters 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.

2) University of Cambridge Campus dataset: [16] 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 the its packets to other nodes so we filtered out the data of the non-participants.

B. 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 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. Our simulator is also mainly based on message exchanges between the nodes. For instance, there is no acknowledgement requirement. Specific protocol related packets (e.g., TCP, UDP) for opening or closing a session are also not taken into account.

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

The outcomes of the proposed routing strategy is compared with epidemic, epidemic with TTS, PROPHET and random routing strategies. Let us briefly describe the routing strategies that are used for analysis in the simulation study. *Epidemic with TTS* is a routing scheme such that each node can only forward certain copies of a given message [17] 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 can not 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. *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 0.1. In *PROPHET* routing strategy, whenever an encounter happens, each node updates delivery predictability (i.e., delivery probability) between itself and its neighbour. P_{init} is set to 0.75, with $\gamma = 0.98$ and $\beta = 0.25$ as suggested in [5]. We empirically set the α parameter of SCR as 0.25 and P_{wanted} parameter of SCR 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.

C. Performance Results

1) Success Rates: 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 Dataset. Although the size of the University of Cambridge dataset is smaller it shows similar results with University of Milano. University of Milano results for success rates fits a curve more than University of Cambridge. The reason can be relatively small size of University of Cambridge data. SCR, epidemic and PROPHET shows very similar message delivery success rates. Epidemic with TTS showed results close to Epidemic, PROPHET and Epidemic with TTS by showing very small difference. Random routing showed the worst results for both of the campuses. 60% or more success rates form about 50% of result data for SCR, epidemic, PROPHET and epidemic with TTS. On the other

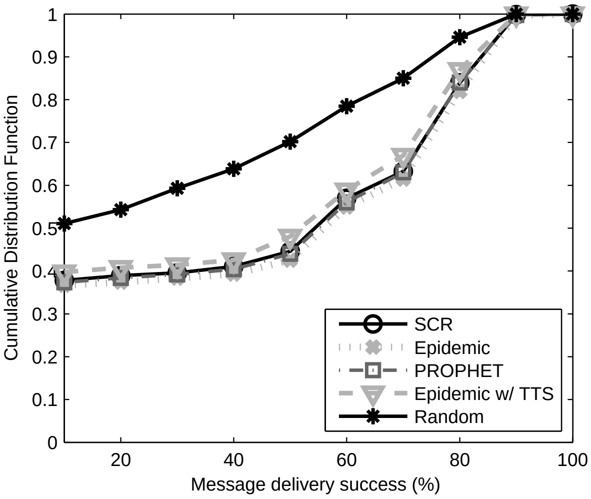

Fig. 3. CDF of message delivery success for the University of Milano dataset.

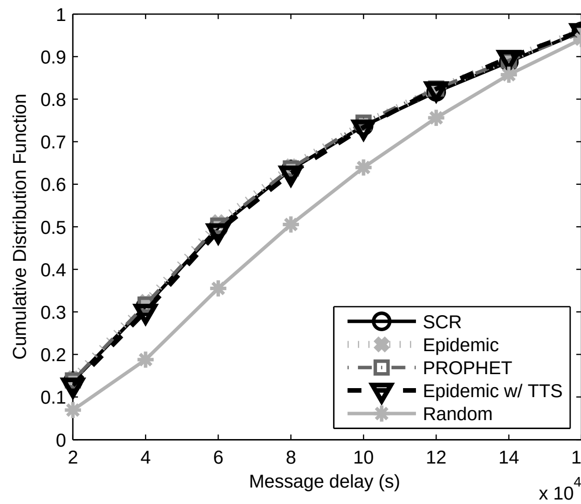

Fig. 5. CDF of message delays for the University of Milano dataset.

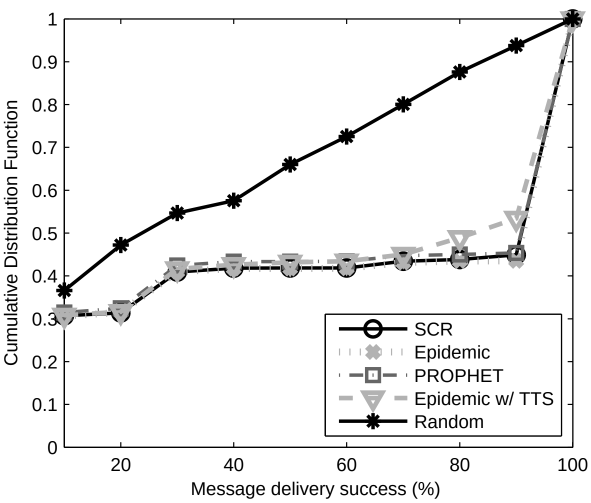

Fig. 4. CDF of message delivery success for the University of Cambridge dataset.

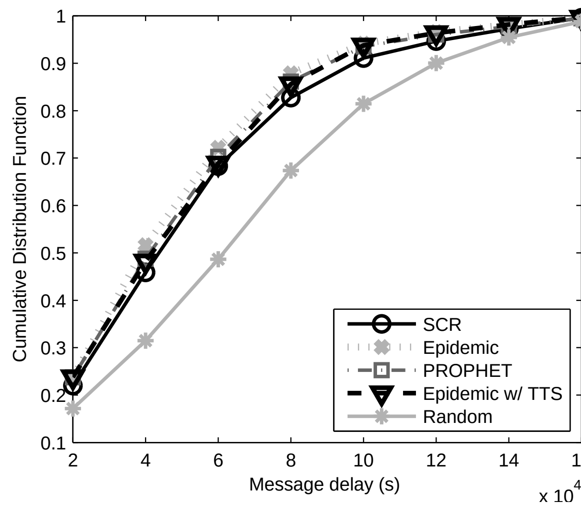

Fig. 6. CDF of message delays for the University of Cambridge dataset.

hand the result data's percentage that contains 60% or more success rates is about 20% for random routing.

2) Message Delays: We continue our discussion of the experimental results with the analysis of the message delay performances. Fig. 5 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 but similar performance in terms of the message delays. Delays more than 85000 seconds (about 24 hours) forms about 45% of the result data of random routing whereas about 35% of the other routing protocols.

We analyze the message delays for the University of Cambridge dataset in Fig. 6. As it can be seen in this figure, SCR, epidemic, epidemic with TTS and PROPHET shows similar message delays. Random routing shows the maximum message delays. On the results of this dataset, the message delays of protocols are not as similar as each other unlike the case in University of Milano. This may be because of again the relatively smaller size of the University of Cambridge data. Delays more than 85000 seconds (about 24 hours) forms about 28% of the result data of random routing whereas about 12% of the other routing protocols.

3) Number of Transmitted Packets: Lastly, we analyze the number of packets that are transmitted among the nodes of the network. Fig. 7 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 25%) amount of packets than the epidemic routing and 20% less than PROPHET. For the University of Cambridge dataset, as shown in Fig. 8, SCR has sent about 30% less amount of packets than the epidemic routing and 20% less than PROPHET. For the simulations done in both of the datasets, epidemic with TTS has a worse performance in terms of packet transmissions compared to SCR and PROPHET. As expected, epidemic has the worst performance due to the fact that data is

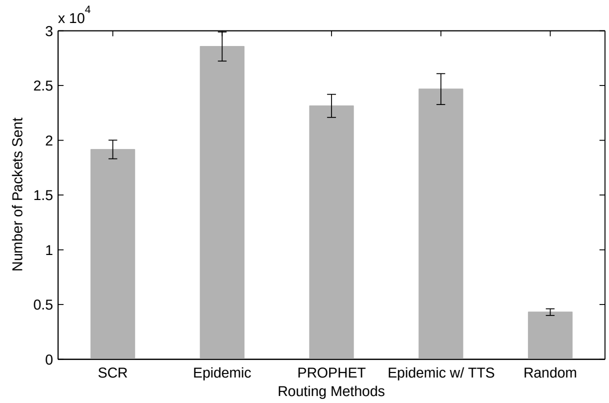

Fig. 7. Number of transmitted packets for the University of Milano dataset.

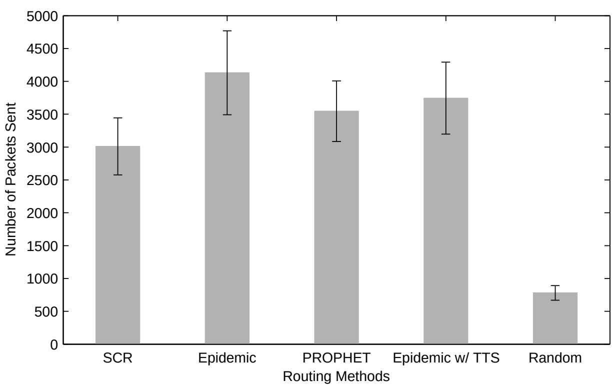

Fig. 8. Number of transmitted packets for the University of Cambridge dataset.

forwarded in every encounter without any limitation. Random routing sent the least amount of packets for both datasets.

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. 7 and Fig. 8. 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. Compared to Epidemic, PROPHET and Epidemic with TTS, SCR has the least amount of packet transmissions for the simulations with both datasets, showing that SCR is the most energy efficient routing protocol among the tested protocols with the two datasets.

VI. Conclusion

In this paper, we propose an opportunistic networking strategy for campus environments. In our application scenario, messages are broadcasted to the students in a university campus via wireless transmission between mobile devices. We propose the SCR protocol for efficiency in terms of number of transmissions, message delays and the delivery success rates. The performance of the proposed approach is analyzed in comparison with epidemic, PROPHET, epidemic with TTS and random routing methods.

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