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SOCIAL POPULARITY BASED ROUTING IN DELAY TOLERANT NETWORKS

Youmei Song, Jianbo Li*, Chenglong Li, Fushu Wang

Institute of Computer Science and Technology

Qingdao University, Qingdao, China

Email: lijianbo@188.com

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Abstract- Due to node's mobility, Delay Tolerant Networks (DTNs) feature the nonexistence of end-to-end path between source and destination, frequent topology partitions and extremely high delivery latency, thus posing great challenges to successful message transmission. To improve routing performance and provide high quality communication service, nodes' social characteristics are exploited to routing design recently. Hence, a social popularity based routing algorithm is proposed, named SPBR which takes the inter-contact time and multi-hop neighbor information into consideration. In this paper, we first introduce a method to detect the quality of relation between pair of nodes accurately. Used the reliable relationships, social popularity is proposed to evaluate the social power of node in the network. SPBR makes the routing decisions based on the popularity, leading message closer to destinations with low hops of routing and network resources. Extensive simulations are conducted and the results show that the proposed algorithm significantly improves routing performances compared to Epidemic, Prophet and First Contact (FC), especially SPBR is lower by about 55.1% in overhead ratio and higher by about 22.2% in delivery rate than Epidemic when there are 40 nodes in the networks.

Index terms: Delay Tolerant Networks; routing algorithm; social group; cohesion; popularity.

I. INTRODUCTION

In traditional networks, the end-to-end paths between source and destination are assumed when nodes deliver messages. However, in most DTN application scenarios, it is difficult to maintain a complete end-to-end path from source to destination due to challenging environment such as sparse node destiny, unpredictable mobility and limited network resources. By implementing the “Store-Carry and Forward” mechanism, opportunistic contacts of nodes are exploited to relay messages hop by hop until meeting the final destination. Thus, the key problem for message delivery in DTNs is to select appropriate intermediate nodes that can provide better delivery performance and consume fewer network resources as next hop relay nodes instead of delivering message to all encountered ones blindly.

J. Ott [1] argues that challenged networking conditions like mobility of node should be regarded as regular case rather than treat them as errors inherently. Since the concept of DTNs was come up with by Kevin Fall firstly, the DTNs architecture [2-4] has been researched widely, which is implemented in different heterogeneous challenged networks such as vehicular Ad-Hoc networks (VANETs) [5-6], Pocket Switched Networks (PSNs) [7], etc. Many researchers find that some DTNs like mobile social networks (MSNs) [8-10] exhibit human behaviors, where mobile users move around, communicate and share data with each other via their mobile devices such as smartphones, laptops, and tablet PCs. Extensive researches have been done and the results argue that human activities have extremely strong regularity, presenting “small-world network” [11-12] phenomenon in ubiquitous personal communication. The social characteristics in specific DTN application scenarios should be exploited accurately for relay selections which have been validated by several social-based routing protocols such as BubbleRap [13], SGBR [14] and CAOR [15].

In social networks, a node usually has complicate social relationships with other nodes rather than being completely isolated because of necessary social daily activities. Take students in a university for example, each student usually spends more time or communicates more frequently with the other students in the same class. And everyone has particular influence because the social skills vary from person to person. The students with more friends have more influence on disseminating messages efficiently and widely. The metrics like centrality have been devised for the purpose of evaluating the social relationship and social role according to their neighbor nodes of individual node. The node with high centrality is bridge and it has a stronger capability of connecting other network members. However, the previous metric's computation only requires the unreliable one-hop connectivity and the neighbor selection is not thoroughly thought out. Due to the complicate connections and random node mobility, routing decision based on these metrics might be unreliable and inaccurate.

The efficient method to select the neighbors can make connection between pair of nodes more reliable. If we just take the nodes who encountered the given node at some time in the past as the neighbors, there would be a big chance in social relation definition. We need connections with high regularity and stability to assess the transmission capability of node. In this paper, we take the inter-contact time into consideration to define neighbors. Inter-contact time is the interval between two successive contacts between pair of nodes. The smaller the inter-contact time of two nodes, the more frequent the encounter. It can reflect the closeness of relationships among the nodes for some time accurately.

What's more, there is a common misleading conception. That is the more direct connections the better in the networks which can work on in all the time. As shown in Figure. 1, which is the simplified local social network, although node i have fewer neighbors than node j, the node i still has higher capability to connect other nodes directly and indirectly than node j. Because the neighbors of node j are isolated while the neighbors of node i are active. Node i can communicate with more other nodes through one-hop neighbors. If source node s who carries message M encounters node i and j at the same time, node i is more appropriate to carry M. Because there are three paths between i and d while one path between node j and d. Hence, who the one-hop neighbors connect with is very essential social characteristic that deserves being exploited carefully. In order to avoid the effects of isolated nodes, we propose a metric called social popularity based on the centrality to evaluate the nodal social influence in the network through the local neighbors of the given node, then a social popularity based routing (SPBR) is proposed. Routing decisions based on the social popularity leads the messages more close to destination with low energy consumption and hops of routing paths.

For the rest paper, we make the following arrangements. In section II, we present some related work. Section III provides the introduction of centrality. In section IV and V, we give a more detailed insight in SPBR. Some network analysis concepts, such as nodes' neighbors and the definition of nodes' popularity, will be presented. In section VI, we conduct extensive simulations and give the detailed performance comparisons. In section VII, we make a conclusion and summarize this paper.

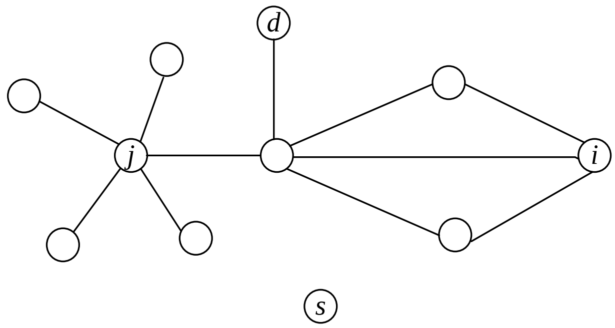


Figure 1. A graph simplified local social network

II. RELATED WORK

Ever since the concept of DTNs has been come up with, there are great contributions for routing design to deal with the challenging task of delivering messages. Epidemic [16] is a classical protocol by implementing the flooding strategy which replicates messages to all encounter nodes blindly so as to maximize the chance to meet the destination. However, the restrictions of node buffer resources and node energy degrade the performance of Epidemic. In order to avoid flooding message blindly, paper [17] proposes Prophet (probabilistic routing protocol using history of encounters & transitivity) which makes use of delivery probability to select relay nodes. The value of delivery probability combining the encounter history information and transitivity is the predictability that relay nodes can deliver message to its destination successfully. And the network overhead of Prophet is hard to be ignored because the utility function of relay selections does not work effectively enough in DTNs. Paper [18] proposes First Contact (FC) routing without depending on topology information in advance. The source nodes carrying message move irregularly and forward messages to neighbor nodes randomly until messages are received by their destination nodes, resulting in a low delivery rate and a high average hop count.

Some researchers take the social characteristic information into consideration and propose some protocols as follows. Bubble Rap is presented based on the concepts of community and centrality of social characteristics. Each node is given two labels that are the measure of node social influence. One is the global rank across the whole network; the other is the local rank across its local community. Message is only allowed to be delivered to the nodes that have higher global rank until the message carriers reach the destination community. The local rank works on selecting the more popularity relay nodes in destination community. SGBR formulate a mathematical model for optimal routing, assuming the presence of a global observer that can collect information about all the nodes in the network. And then they propose a new protocol based on social grouping among the nodes to maximize data delivery while minimizing network overhead by efficiently spreading the packet copies in the network. Mingjun Xiao etc. propose a home-aware community model, whereby they turn an MSN into a network that only includes community homes. They coordinate a home-aware community model and a reverse Dijkstra algorithm used to compute the minimum expected delivery delays of nodes, propose a distributed optimal community-aware opportunistic routing (CAOR) algorithm. All above algorithms need the knowledge of the information of the network topology, and the manners of relay selections are very complicated.

III. CENTRALITY

The kinds of ties among nodes are various in social networks. Centrality is a concept that is used to identify the social importance of a certain node. A node with high centrality means that it has strong capability of connecting other nodes or locates in a key position to control the information flow. There are many ways to measure centrality value and the universally used metrics are described as follows.

(1) Degree centrality (DC). Degree centrality is the simplest centrality metric defined as the number of direct neighbors connected in history of the given node. If the given node has high degree, it would be regarded as a powerful node in a network. It seems that the more connections the given node has, the more powerful it is. However, the degree centrality extraction only relies on the 1-hop connections, which is more insubstantial for message transfer. In Figure 1, although node j has the higher degree centrality than node i, the capability of delivering message is inferior to node i.

(2) Betweenness centrality (BC). Betweenness centrality measures the capability of controlling information flowing in the networks. It estimates the number of shortest path through a given

node. High betweeness centrality means that the given node locates an important position in topology graph so that it can facilitate communications with other nodes. As shown in Figure 1, node *j* has advantages in betweenness centrality compared to node *i*.

(3) Closeness centrality (CC). The node with highest closeness centrality usually has the shortest paths to all others. That is to say, it is closest to other nodes in the network. These nodes can spend the least time spreading information to other nodes. In general, the node with prominent closeness has better visibility and monitors information flow more easily and accurately. Node *j* has the shorter overall paths to the rest of the nodes compared to node *i* shown in Figure 1.

Table 1 shows the respective centrality measures of node *i* and node *j* according to Figure 1. It is obvious that node *j* has prominent advantages compared to node *i* in terms of degree centrality、betweeness centrality and closeness centrality. However, the probability of node *i* transferring message to node *d* is higher. This is because the isolated neighbors of node *j* degrades its capability of message transmission, while the active neighbors of node *i* result in more paths from node *i* to *d*. Although centrality might play an important role on the relay nodes selection for when、what、where to cache data and for how long, the existence of isolated nodes is likely to mislead the value of it. To deal with the defects of centrality, we present a new metric called social popularity. The details will be provided in the next section.

Table 1. Centrality of node *i* and *j* in Figure 1.

	Degree centrality	Betweeness centrality	Closeness centrality^{-1}
Node *i*	3	0.5	19
Node *j*	5	26	13

IV. SOCIAL TIE DETECTION

Topology control with certain properties (e.g. choosing the right neighbors to pass messages) can make the goal to bring down energy consumption and maximize message delivery ratio. Social relationship among mobile nodes is usually long term characteristic and less volatile than node mobility. To obtain the high quality social relationship, we define neighbor node as some nodes encounter the given node frequently in the past time. In this section, we firstly consider operating a new approach to select the neighbors to form the high quality social graph, and then detect popular nodes which have stronger capability of connecting other members in the network.

a. Social Graph Aggregation

The aggregated social graph $G=(V, E)$ is an efficient way to describe the complicated social relationship in DTNs so as to overcome the intermittently connected physical topology, where V and E denotes mobile node set in the network and the mutual relationship set among nodes respectively. The social graph isn't defined as usually where the historical encountered nodes are all added into V_i. In this paper, only the neighbors whose relationships with the given node are stable and reliable are used for detecting the popular or central node in the network. At the same time, to accurately obtain the high-quality social graph for efficient routing selection, aggregating historical contact information of related nodes is basically.

In a social network, each link representing social relation in the social graph is associated with a weight. Due to some social activities, everyone can't be familiar with all others. For example, we spend more time to stay with family or colleagues or communicate with them more frequently. On the contrary, we have little chance to communicate with the strangers. Inspired by this, we filter out a node's random connections and keep the neighbors who have stable and reliable relationship with the given node to make the message delivery more sensible. In other word, not all connections can be added into the edge vertex in social graph, but only the connections that their strength is higher than the threshold we set in advance.

To distinguish neighbors and random encounters, one way is to estimate their similarity values by measuring historic shared encounter nodes of pair of nodes. The inter-contact time is the other way to estimate the connection strength between encounters. In this paper, we assume that inter-contact time between two mobile devices follows a power law which has been studied in [19-20]. The parameter of power law α also called the heavy tail index reflects the closeness degree of relation of pairs of nodes. And we consider the heavy tail index for edge weight calculation. The parameter α for each pair is different because the social relation of every pair node is heterogeneous. Hence, evaluating the value of this coefficient accurately is propitious to filter the neighbors from random connections.

1) Estimator for the coefficient of power law. We give every node with a list to record the inter-contact time with other nodes which are arranged in ascending order. For easy to describe, we only consider the coefficient calculation method of a pair of nodes, others' are with the same as above. Considering a pair of node i and j, X_1 X_2 …, X_n are used for denoting the increasing inter-

contact times of node i and j observed during time T. Since we have made the assumption that the sample of inter-contacts follows a power law with coefficient $\alpha_{i,j}$, we have the probability that the inter-contacts X between node i and j is higher than a certain value X_k:

$$P(X \geq X_k) = X_k^{-\alpha_{i,j}} = \frac{n-k+1}{n} \tag{1}$$

And then $\alpha_{i,j}$ can be estimated by the following formula:

$$\alpha_{i,j} = \frac{\ln n - \ln(n-k+1)}{\ln X_k} \tag{2}$$

The value of $\alpha_{i,j}$ among all pair nodes ranges between 0 and 1. Different heavy tail index for pairs of nodes reflects the heterogeneous social relationships among nodes. Social relationship is positively correlated with the value of heavy tail index. In other word, the higher α, the less inter-contacts between two nodes, the more stable and reliable the relation of pair of nodes is.

2) Neighbor node detection. We give an experimental constant τ to be regarded as the selection criteria of neighbor node. The social relation between node i and j would be included to edge set E of social graph, if the value of heavy tail index among them is higher than τ, that is,

$$l_{i,j} = \begin{cases} 1, & \alpha_{i,j} > \tau; \\ 0, & \alpha_{i,j} \leq \tau \end{cases} \tag{3}$$

To extract the local topology information conveniently, we exploit an $n \times n$ adjacency matrix A^i to reflect the relations among node i and its n-1 neighbors. The element of adjacency matrix $a^i{}_{kl}$ denotes the relationship between node k and l. $a^i{}_{kl} \in \{0,1\}(k,l \leqslant n)$, the node is either neighbor of the given node i ($a^i{}_{kl}$ is represented by a value 1), or is not ($a^i{}_{kl}$ is represented by a value 0). Once node i contacts others so frequently that the connection strength satisfies the neighbor selection standard we defined before, the matrix $A^i{}_{n \times n}$ and social graph G will be update immediately to ensure the social tie detection accurately.

b. Popularity definition

The characteristics of individual neighbors deserve costing high price to be exploited for message delivery. The neighbors' connection is important factor for next possible relay selection. It is straightforward to transfer messages based on only one-hop connection information. The isolated neighbors affect the node's real transmitting capacity. Arbitrary two neighbors of the given node may know each other and even have deep relationship, reflecting the cohesion degree among neighbors in some extent. From Figure 2, we can see that even though the connection between node *i* and node *a*, node *i* still can transfer message to node *a* through node *b*. But if the link between *b* and *e* failed, node *b* could lose chance to connect node *k* and *l*. High cohesion among the neighbors infers that there could be many possible paths to the rest nodes of network. In other words, the neighbors' capability of connecting others takes an effect on the given node propagating the message widely. Although the degree centrality is also used to assess the node social influence, only considering one-hop information is unreliable. Thus metric called node popularity based on degree centrality and cohesion among neighbors is proposed so as to select the relay node more efficiently.

We assume that the neighbor set of node i Nei_i have k_i elements. If every two neighbor nodes has an edge, the number of the edges among the neighbors Nei_i would be:

$$k_i(k_i - 1)/2 \qquad (4)$$

However, the above situation where Nei_i has the most edges of node *i* cannot be possible in practical networks. For example, a student knowing each other students and teachers in university is unreasonable in realistic environment. So the element of adjacency matrix a^i_{kl} can't be all 1. Any two neighbors of node *i* exists a link, they can form a triangle by one of the vertices *i*. In other words, suppose that message *M* starts from node *i* and arrives at node *i* finally after 3-hops transmission, then there would be a path triangle in social graph if we connected the three different nodes. The more triangles by vertex node *i* there are among neighbors, the stronger solidarity level of social group is. Thus we use the number of triangles to measure the cohesion of each node.

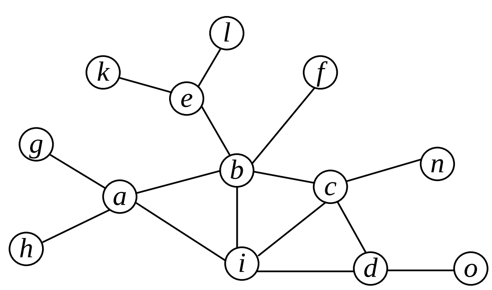


Figure 2. Popularity of node *i* and *b*

Matrix multiplication is a widely used mathematical operation in social network analysis, which is exploited to research the numbers of walks or the reachability between nodes. In last section we have defined the efficient relation selection standards by introducing the power-law distribution model and adopted an $n \times n$ adjacency matrix A constituted of 0 and 1 to express the relations in correlative local social neighbors. Take the undirected graph of Figure 2 which describes the local social information of node i and b for example. The 5×5 adjacency matrix B^i of node i extracts the intricate and complicated relations among node i's neighbors.

	i	*a*	*b*	*c*	*d*
i	0	1	1	1	1
a	1	0	1	0	0
b	1	1	0	1	0
c	1	0	1	0	1
d	1	0	0	1	0

From the adjacency matrix $B^i_{5\times5}$, we can find that whether there are close connection between pairs of nodes expediently and directly. If we calculate the square of $B^i_{5\times5}$, we have:

	i	*a*	*b*	*c*	*d*
i	4	1	2	2	1
a	1	2	1	2	1
b	2	1	3	1	2
c	2	2	1	3	1
d	1	1	2	1	2

The elements of $B^i \times B^i$ represent the number of the 2-hop paths among neighbors of node i. For example, there are 4 paths from node i to itself through two-hop relays in Figure 2, we list the detailed paths as follows.

$$i \to a \to i\,;\, i \to b \to i\,;\, i \to c \to i\,;\, i \to d \to i$$

And the number of paths between node i to itself coincides with the value of first element of square matrix $(B^i)^2$. Further, we define $W^i_{n\times n}$ to stand for $B^i_{n\times n} \times B^i_{n\times n} \times B^i_{n\times n}$, then we can obtain the number of 3-hops paths between neighbors of node i's, or the cohesion degree among the neighbors. Thus, we use the three power of matrix to define the number of path triangles by vertex i E_i:

$$E_i = \frac{1}{2} w^i_{ii} \tag{5}$$

Then, we give the specific definition of popularity P_i of node i using the value of E_i:

$$P_i = \frac{2E_i}{2\sum_{m\in Nei_i}^{|Nei_i|}\sum_{j=1}^{N} l_{m,j} - \sum_{k,l=1}^{k,\ l=|Nei|} w^i_{k,l}} \tag{6}$$

N represents the number of all nodes in the network; the former of the denominator is the sum of degree of node i's neighbors and $\sum_{k,l=1}^{k,l=|Nei|} w^i_{k,l}$ is the sum of $W^i_{n\times n}$'s elements. Then from the Figure 2, we can calculate the value of E_i and P_i:

$$E_i = 3$$

$$P_i = \frac{3\times 2}{2(4+5+4+3+4)-14} = \frac{3}{13} \approx 0.23$$

By the same method of popularity calculation, we have:

$$P_b = \frac{4}{(4+1+4+4+4+5)\times 2-14} = \frac{1}{7} \approx 0.143$$

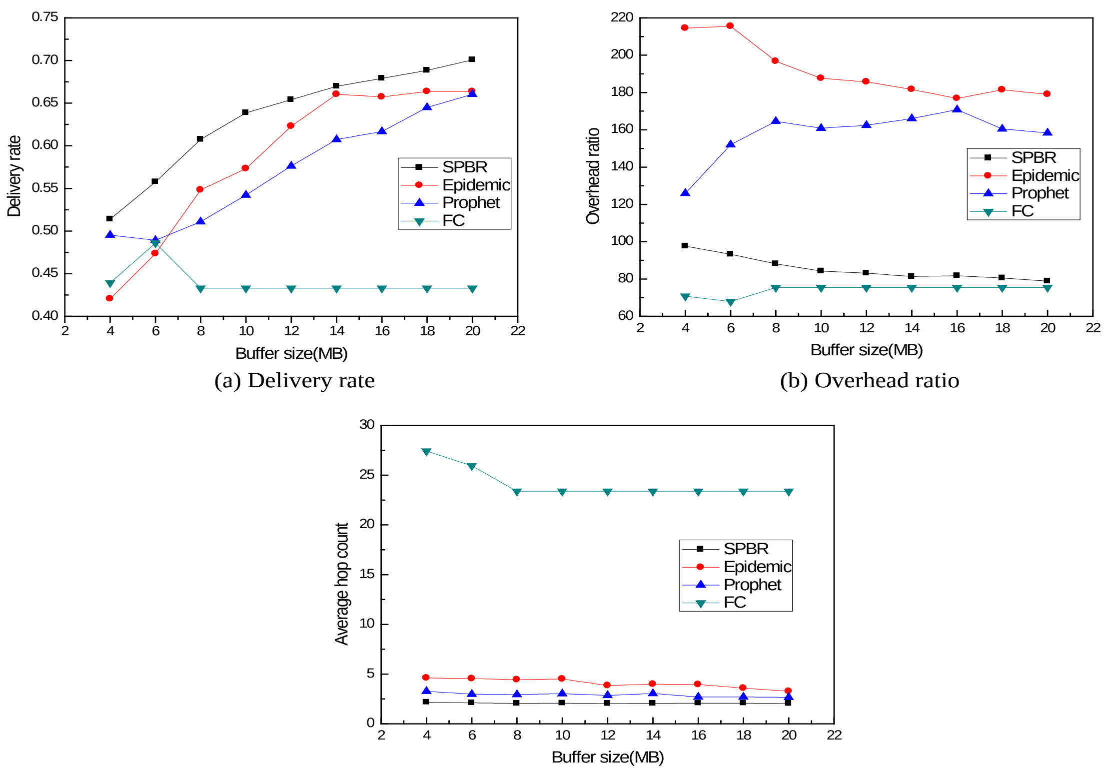
Algorithm 1: SPBR Algorithm, pseudo-code of node *i* upon meeting node *j*, destination *d*

```
procedure Select neighbors
  j.lastTime ← currentTime
  update intervalTimeQueue(j)
  update α_{i,j}
    if α_{i,j}>τ
      update G
      update P_i
    end if
end Procedure
Procedure Select message carrier
 exchange neighbor set Nei
  if d is the neighbor of nodes in Nei_j && P_j>P_i
    copy message to node j
  else if d isn't the neighbor of nodes in Nei_j &&P_j<P_i
    copy message to node j
  end if
  end else if
end Procedure
```

Formula (6) can not only reflect the cohesion of the node i among its neighbors, but also reflect the ability of spreading messages from node i through its neighbors, indirectly. If the isolated neighbors represent a much higher proportion of all neighbors, there would be small number of circular paths. This is not propitious to transfer message widely because the links are unstable. Considering the destination location, we will make different routing decisions based on node popularity. On the one hand, to spread the message widely, we avoid transfer message to node with high popularity when the destination locates far away. One the other hand, the node with high popularity is a promising next relay when the destination have close the relationships with the neighbors, because more possible paths between the given node and the destination can improve the probability of successful message transmission which enhances the message delivery rate.

Table 2: Parameter settings of simulation

Parameter	**Default Value**	**Range**
Area size(m×m)	4500×3400	--
Number of nodes	--	40-60
Initial topology	Uniform	--
Transmit radius(m)	20	--
Message size(KB)	500-1024	--
Message interval(s)	90	50-90
Transmit speed(KBps)	250	--
Moving speed(m/s)	0.5-1.5	--
Node buffer size(MB)	16	4-20
TTL(min)	240	90-330
Simulation time(h)	12	--

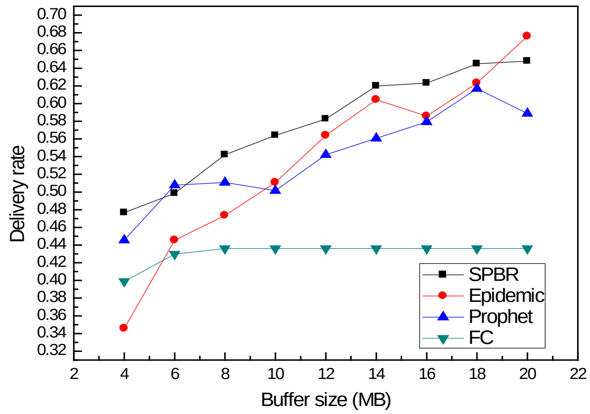


(a) Delivery rate

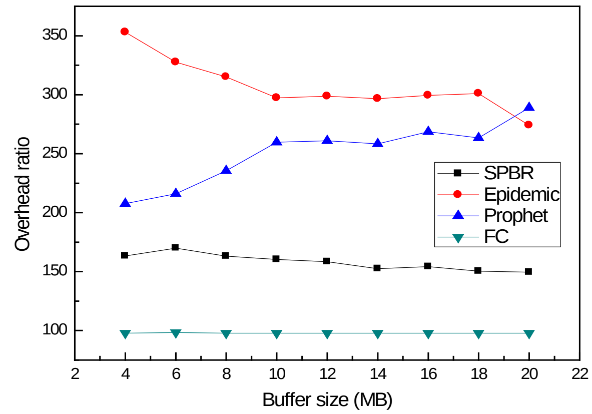
(b) Overhead ratio

(c) Average hop count

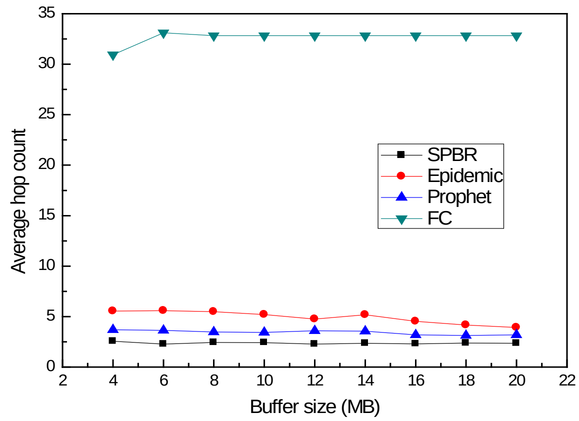
Figure 3. Simulation results of varying the buffer size with 40 nodes



(a) Delivery rate



(b) Overhead ratio

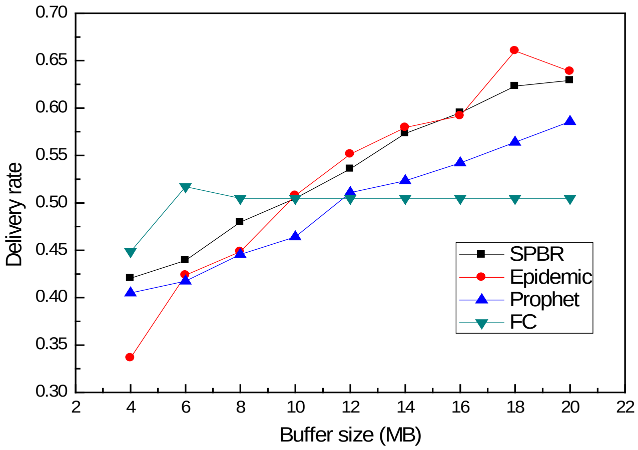


(c) Average hop count

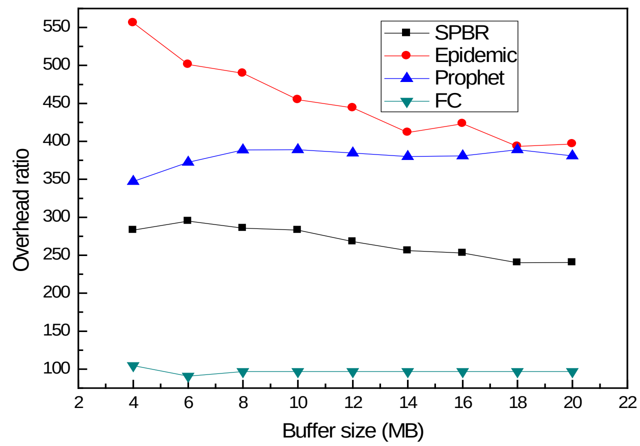
Figure 4. Simulation results of varying the buffer size with 50 nodes

V. ROUTING

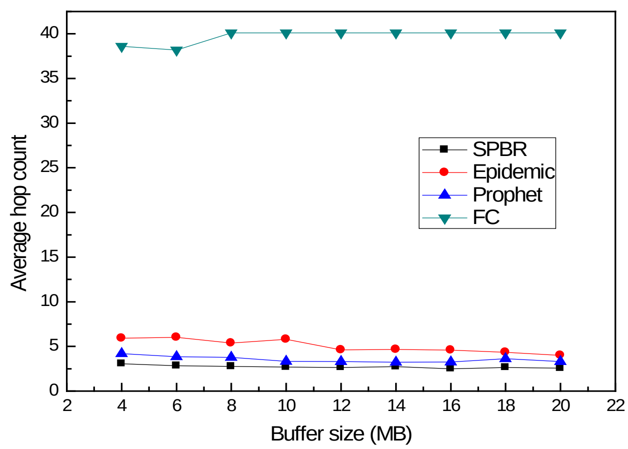
Algorithm 1 gives the possible choice of two encountering nodes, *i* and *j*. There are two principles to make routing decisions. The first one is that we select the node with higher popularity if the neighbors' reliable connections contain the destination nodes to increase the probability of delivery. However, strong cohesion causing circuitous routes among neighbors probably obstructs the widely dissemination of message. The neighbors with higher degree which brings down the node popularity can also make the given node more popular after the neighbors' relay broadcasting. Then the second principle is to select the node with lower popularity but high degree of neighbors as the next message relay when destination node is at a distance more than three hops from the given node. This avoids wasting energy in delivering messages to improper candidates. All strategies are aim to make packet closer to the destination node quickly, increasing delivery rate and reducing overhead ratio.



(a) Delivery rate



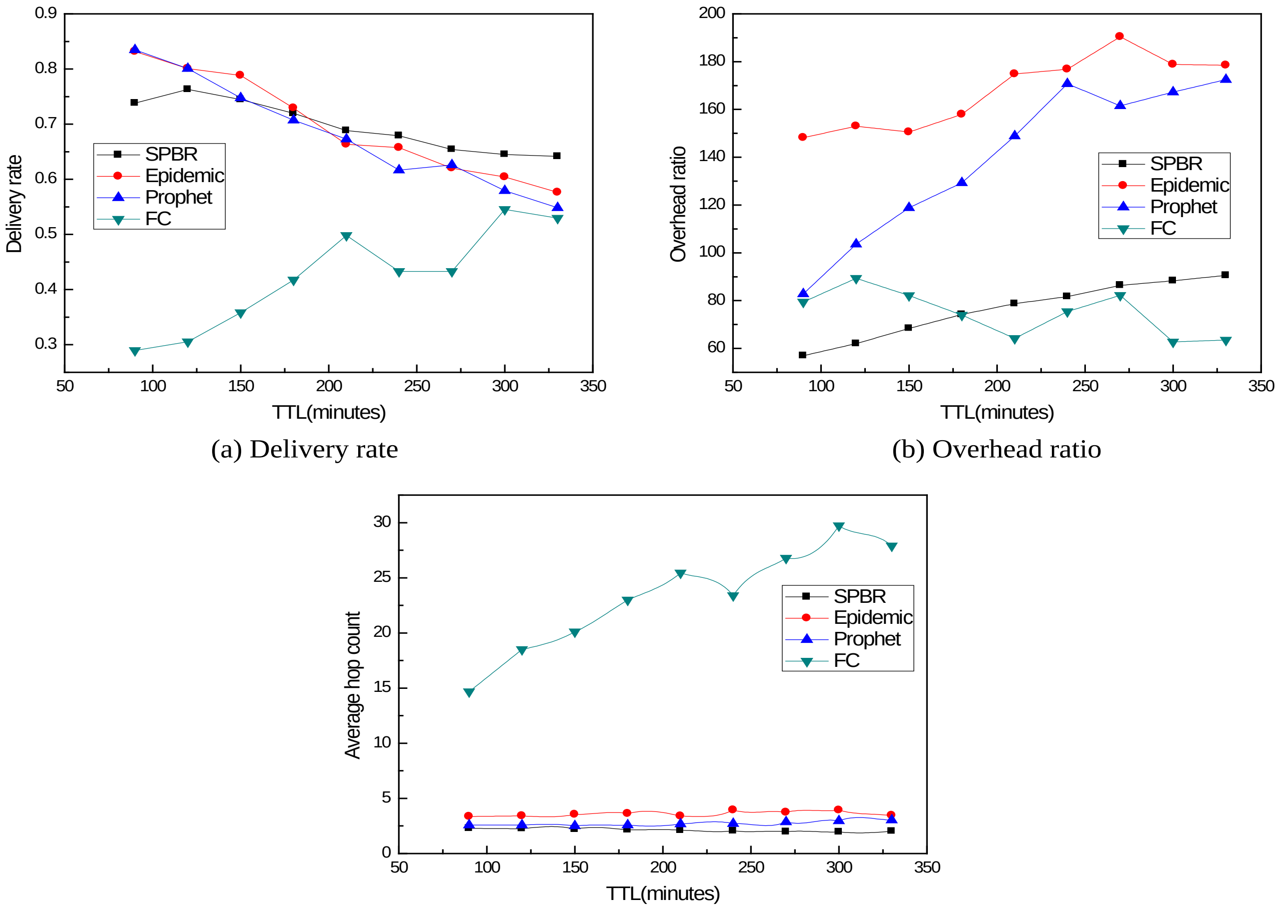
(b) Overhead ratio



(c) Average hop count

Figure 5. Simulation results of varying the buffer size with 60 nodes

The detailed routing strategies are illustrated in algorithms 1. Each node maintains a neighbor node table. Consider d as the message M's destination. When current node i encounters node j, they should exchange their neighbor information. The encounter time should be recorded and we need update the inter-contact time list if they have met more than once. Then the list of inter-contact time is used to update the link weight of node i and j by the formula (2). If the heavy tail index satisfies the selection standard of neighbor, the social graph and popularity of node i will be updated as lines 5-7 by the formula (6). In lines12-16, the routing decision is made upon the node popularity. If d is the close connection of node j's neighbors and P_j is higher than P_i, then we deem that node *j* is a better message carrier than *i* because strong cohesion among the neighbors promotes node *j* to deliver the message with high probability. On the other hand, if node *d* does not reside in the connections of *j*'s neighbors nearly, we copy message to the node *j* that has the lower popularity with the routing aims to spread message widely.



(a) Delivery rate

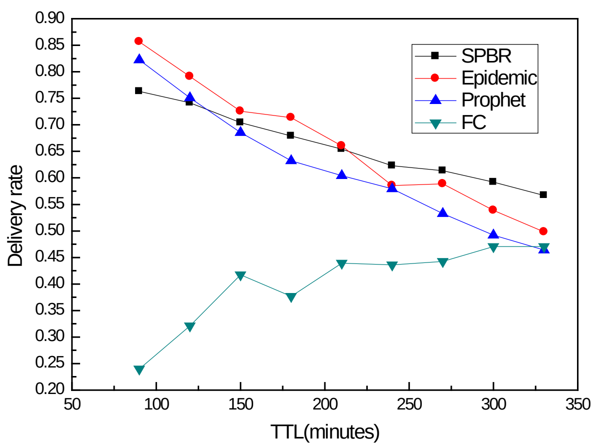
(b) Overhead ratio

(c) Average hop count

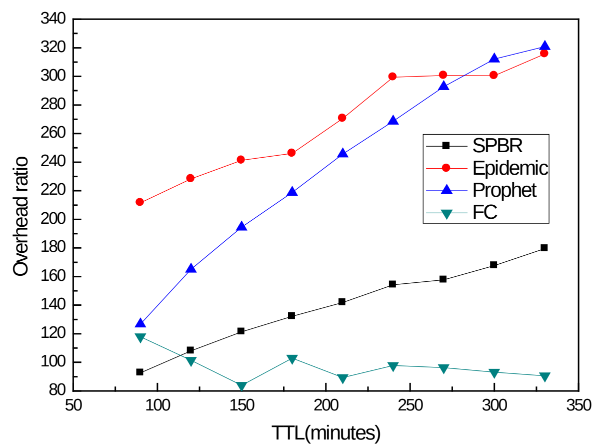
Figure 6. Simulation results of varying the message TTL with 40 nodes

VI. EVALUATION

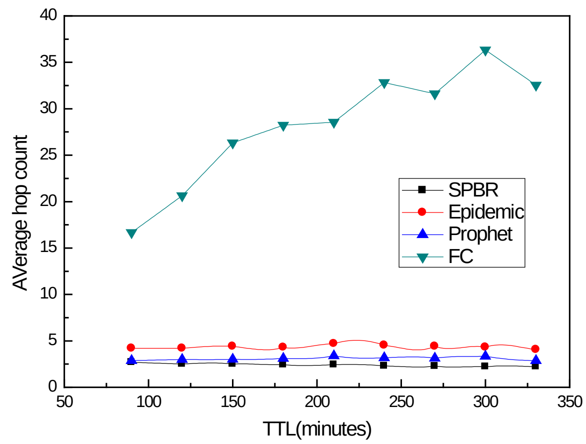
The Opportunistic Network Environment (ONE) [21] is adopted to evaluate the effectiveness of our proposed connection utility metrics based on aggregated social graph, with using the real trace and synthetic mobility model. The number of nodes in network scenario is an important factor to affect the performance of algorithm. The more nodes there are in the networks, the more complicate social relations are. We compare our protocol to the Epidemic, Prophet and FC under the network scenarios where set the number of nodes to 40, 50 and 60 respectively in the following categories: (1) performances of each method under different buffer size; (2) performances of each method under different message TTL; (3) performances of each method under different message interval. Table 2 shows the parameter settings in detail.



(a) Delivery rate



(b) Overhead ratio



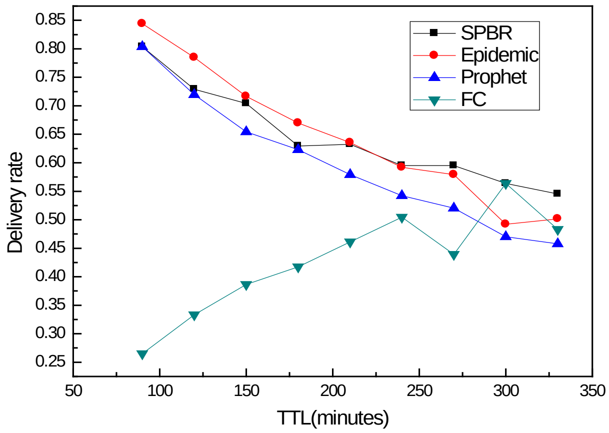
(c) Average hop count

Figure 7. Simulation results of varying the message TTL with 50 nodes

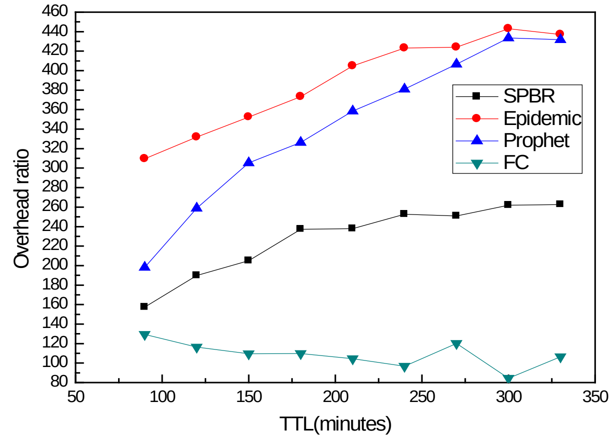
a. Evaluation with different buffer size

Figure 3 demonstrates the performances of four methods by altering the buffer size from 4MB to 20MB under scenarios with 40 nodes. And for the fair of the comparison, the message TTL is maintained constant at 240 minutes and the message interval is maintained constant at 90 seconds. Along with the increasing of buffer size, the probability of dropping message because of the limited buffer decreases reduces. Then the capability of nodes carrying message becomes stronger, all evaluated methods present a trend of increasing in delivery rate. Compared with

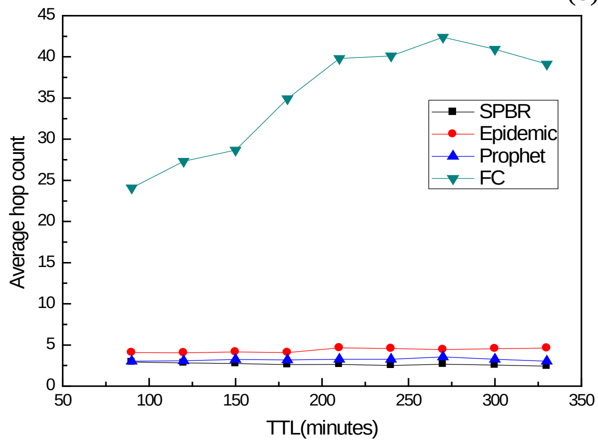
Epidemic and Prophet, SPBR increases the delivery rate by 22.2% and 18.9% at the most, and decreases the overhead ratio by about 55.1% and 45.2%, respectively in Figure 3(a) and (b). In Figure 4(a), when buffer size is 19MB, SBPR is caught up with by Epidemic. From Figure 5(a), Epidemic is inferior to SPBR before the buffer size is 10MB, and then they are almost on a par.



(a) Delivery rate



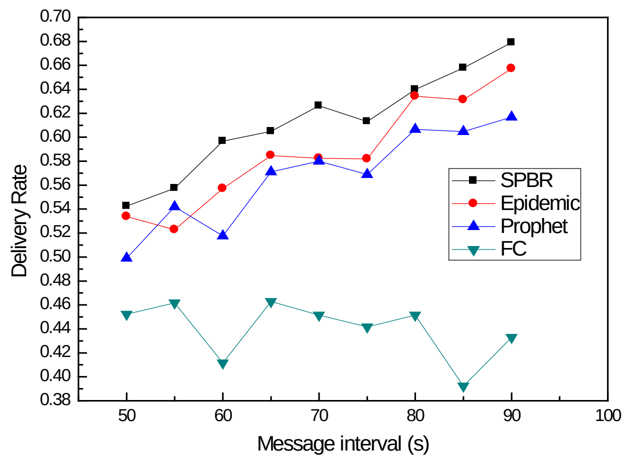
(b) Overhead ratio



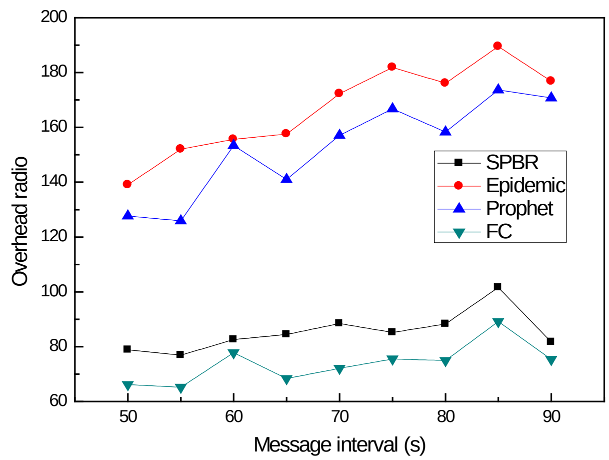
(c) Average hop count

Figure 8. Simulation results of varying the message TTL with 60 nodes

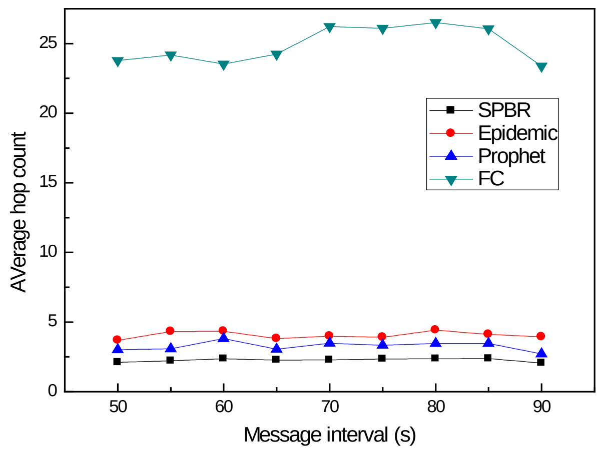
When the buffer size is not limited, Epidemic routing outperforms the others in delivery rate due to its flooding strategy at the expensive of consuming large network energy. However, SPBR is superior to Epidemic in delivery rate and overhead ratio in the real network scenario where the buffer is limited. What's more, no matter how the buffer size and number of nodes change, SBPR also keeps on lower level in overhead ratio and average hop count due to the effective routing strategies based on node popularity. FC selects a neighbor node randomly to forward message, leading lowest overhead ratio and highest average hop count in Figure 3-5 even though there is enough buffer size.



(a) Delivery rate



(b) Overhead ratio

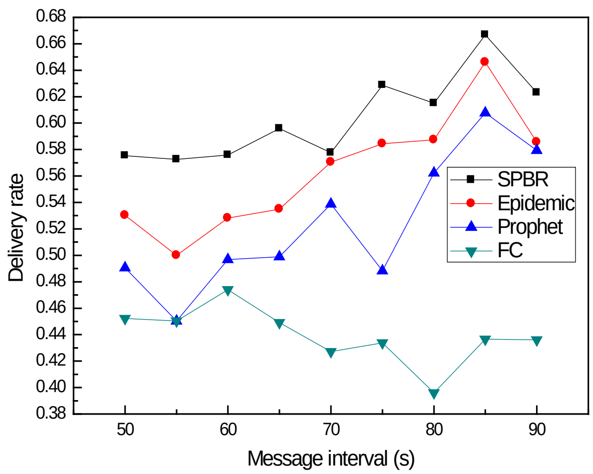


(c) Average hop count

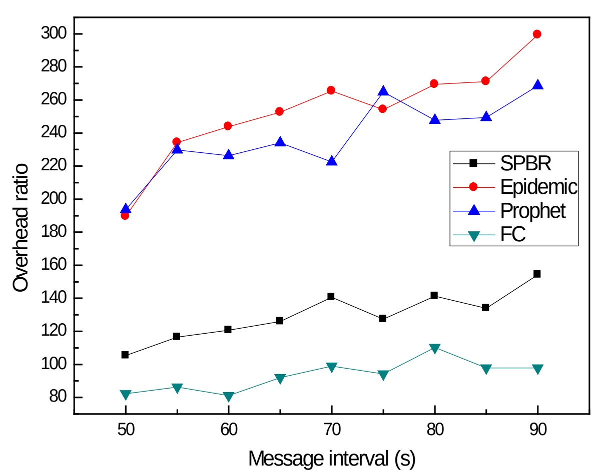
Figure 9. Simulation results of varying the message interval with 40 nodes

b. Evaluation with different message TTL

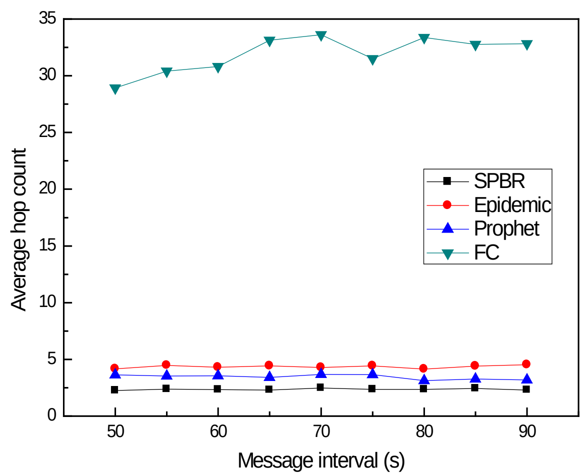
Figure 6-8 shows the influences of message TTL (time to live, TTL) to abovementioned algorithms. Node buffer size and message interval are set to fixed values 16MB and 90 seconds. Message is efficient only during its TTL. With the growth increment of 30 minutes, the messages have longer survival time if they aren't discarded due to insufficient buffer size. However, node buffer size is subject to the practical installation restrictions, longer message TTL aggravates the already serious shortage of network energy. The theoretical analysis results are validated by Figure 6, 7 and 8. With the increment of message TTL, although the curved shapes representing delivery rate almost present a downward trend except FC, SBPR becomes superior to other routing algorithms in delivery rate when message TTL is about 210 minutes, 240 minutes and 270 minutes in Figure 6(a), 7(a) and 8(a), respectively. At the same time, SPBR holds on to the favorable position in overhead ratio. What's more, SPBR almost stains 3 hops from source nodes to destination nodes even with the high message TTL. This is because our proposed routing methods select next relay nodes according to node cohesion in its local social clustering. From Figure 6-8, we can see that SPBR is more suitable to work in the large networks with high message TTL.



(a) Delivery rate



(b) Overhead ratio

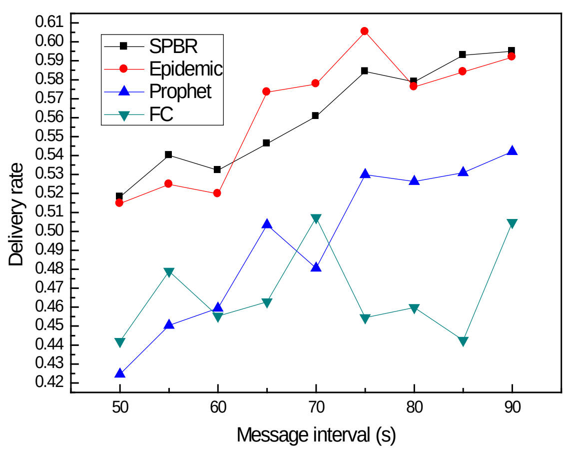


(c) Average hop count

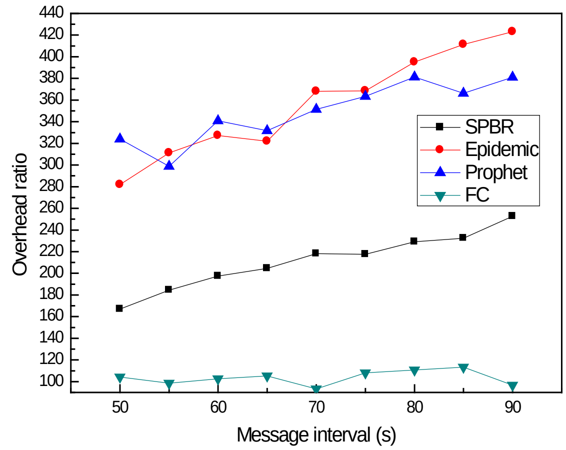
Figure 10. Simulation results of varying the message interval with 50 nodes

c. Evaluation with different message interval

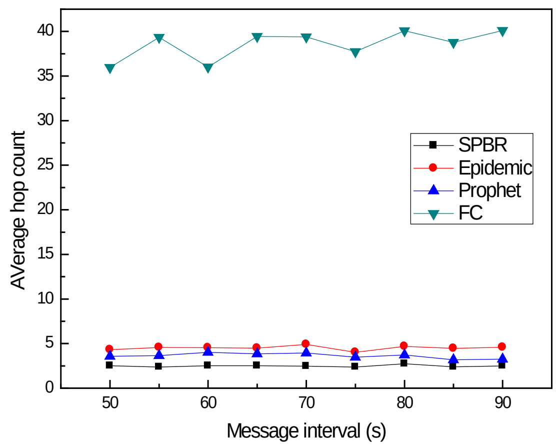
The results of simulation under the circumstances where the message interval is changeable are similar to the simulation results of changeable buffer size and message TTL. Overall performances of SPBR are better than other three routing algorithms'. From Figure 9(c), 10(c) and 11(c), node average hop count is effectively controlled to response the changes of message interval and number of nodes in the networks. When the message generation interval is short, the message delivery rate of all the four routing algorithms is low, since that there are a large amount of generated messages occupying the nodes' buffer, which causes messages dropped frequently.



(a) Delivery rate



(b) Overhead ratio



(c) Average hop count

Figure 11. Simulation results of varying the message interval with 60 nodes

With the increment of message interval, the message delivery of all methods arises and SPBR almost has the same high delivery rate as Epidemic in scenario with the number of nodes being 60. At the same time, the cured shapes representing message delivery rate and overhead ratio of SBPR fluctuate narrowly with changing message interval, reflecting that our proposed routing methods can effectively select fewer but more appropriate intermediate nodes to delivery messages by adjusting routing measures according to node popularity. What's more, SPBR performs better than Prophet from the whole point of view, meaning that Prophet selecting the relay nodes based on probability is less effective than SBPR selecting relay nodes based on popularity. From Figure 9-11, we can see that SPBR can adapt to the changeable message interval.

VII. CONCLUSION

The routing decision is hard in DTNs due to the dynamic topology. To lead the message closer to the destination with low energy consumption and high delivery rate, SPBR is proposed which takes full advantage of the social characteristics. In this paper, we firstly propose a method to select node's neighbors so as to construct a high quality social graph. By exploiting the constructed social graph, we define a hybrid metric called popularity to detect the influence of node in the network. Node popularity not only implies that the given node's capability of uniting its neighbors, but also can estimate how widespread the message can be transferred after two-hop relays. Then we proposed two routing strategies based on node popularity in order to reduce network resource consumption and increase messages delivery ratio. Extensive simulations are conducted and the results show that the proposed routing algorithm works efficiently. SPBR outperforms the other classical routing algorithms in terms of delivery rate, network overhead and average hop count. In the next work in the future, we will concentrate on detecting the other social ties like social community so as to improve routing performance in DTNs.

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