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Effective Forwarding Scheme for Opportunistic Networks Based on Refined Contact Probability and Betweenness Centrality

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When forwarding in opportunistic networks, the higher contact probability that the destination node has, the more likely it is to forward a message to the destination. Moreover, the higher the betweenness centrality that a node has, the more likely it is to act as a bridge node toward the destination in the network. Each of these two metrics is exploited in existing forwarding schemes. Nevertheless, these schemes suffer from high network traffic and fail to balance network traffic and transmission delay while maintaining a lower hop count. To resolve these problems, we propose a novel forwarding scheme that considers refined contact probability and betweenness centrality. In the proposed scheme, nodes with higher probabilities of contact with other nodes tend to gather together, while nodes with higher betweenness centralities compensate for intermittent connection disruptions among nodes in the network. Experimental results show that the proposed scheme outperforms most known forwarding schemes in balancing network traffic and transmission delay.

Keywords: opportunistic network, OPPNET, forwarding, probability, centrality, betweenness

1. INTRODUCTION

Recent advances in wireless communication technologies have enabled opportunistic networks [1] (OPPNETs) − also known as pocket switched networks [2] to rapidly emerge. Owing to the popularity of mobile devices, OPPNETs have been widely studied and have various applications, such as the Sami Network Connectivity Project [3], ZebraNet [4], Shared Wireless Info-Station [5], and others. OPPNETs have inherited the characteristics of both mobile ad hoc networks (MANETs) and delay-tolerant networks (DTNs), thereby adding the social properties of mobile nodes communicating with each other within short communication ranges in sparse environments. The OPPNETs suffer from intermittent connection disruptions and long delays due to low node density, short communication ranges, and node mobility.

In particular, because there may be no stable route between the source and destinations [1], conventional forwarding schemes used for MANETs are not applicable; thus forwarding is a challenging problem for OPPNETs. Hence, nodes communicate with multiple hops in a store, carry, and forward manner in OPPNETs. When a node cannot find any nodes within its communication range, it should take any contact opportunity

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with other nodes to forward the messages [6]. Therefore, it is crucial to find suitable nodes that can play the role of stepping stones in forwarding a message to the destination.

Clearly, the higher the contact probability that a node has with respect to the destination, the more likely it is to forward a message to the destination. Moreover, the higher the betweenness centrality that a node has, the more likely it is to act as a bridge node toward the destination in the network. Contact probability and betweenness centrality are exploited in existing forwarding schemes, such as ProPhet [21] and SimBet [16]. ProPhet uses "delivery predictability" to describe the contact probability of how frequently a node meets other nodes, whereas SimBet combines social similarity and betweenness centrality for forwarding. However, they suffer from higher network traffic and fail to balance network traffic and transmission delay while maintaining a lower hop count.

Limited resources such as bandwidth, power consumption, channel utilization, and network size exist; therefore, the nodes suffer from some communication difficulties. Hence, network problems such as bottlenecks, slow communication, and noise problems may occur as network traffic increases. Even though applications in OPPNETs should be relatively delay-tolerant, it is nevertheless important to minimize the delay whenever possible. Finally, because hop count can be used to limit the resource utilization of nodes, it can be additionally regarded as an important metric for the performance measure.

To resolve the above problems, we propose an effective forwarding scheme that considers refined contact probability and betweenness centrality (RCPB) and integrates them with social information obtained from the home-cell community-based mobility model (HCMM) [7]. We refine contact probability by considering the frequency, longevity, and regularity of node contacts [24]. This is because the more frequently they encounter each other, as well as the longer and more regularly they meet, the higher the contact probability will be that they attain.

In the RCPB model, nodes with higher probabilities of contact with other nodes tend to gather together, while nodes with higher betweenness centralities compensate for the intermittent connection disruptions among the nodes in the network. RCPB appropriately integrates both metrics to successfully reduce network traffic while maintaining acceptable transmission delays and lower hop counts.

The main contributions of the paper are summarized below.

(1) We propose a novel forwarding scheme that integrates both the refined contact probability, considering the frequency, longevity, and regularity of node contacts, and betweenness centrality
(2) We use the network simulator NS-2 v2.35 [29] for simulations on the HCMM. The simulation results show that the proposed scheme outperforms most forwarding schemes, including Epidemic, Wait, SimBet, and ProPhet, as well as pure centrality-based schemes that use degree, betweenness, and closeness centralities.

The remainder of this paper is organized as follows. In Section 2, we discuss related work. After describing the system model and assumptions in Section 3, we introduce the proposed scheme in Section 4. The simulation environment and results are shown in Section 5. Finally, our conclusions and suggestions for future work are provided in Section 6.

2. RELATED WORK

Conventional routing schemes for MANETs include Dynamic Source Routing, the Ad Hoc On-Demand Distance Vector, Split Multipath Routing, the Shortest Multipath Source, and AntHocNet [8]. A double-layered peer-to-peer system using clustering was also introduced for routing performance [9]. However, none of these schemes can be directly useful for OPPNETs, regardless of improved performances, because there may be no stable route between the source and destination in OPPNETs.

In OPPNETs, forwarding/routing schemes can be categorized in two groups: zero knowledge schemes and non-zero knowledge schemes. Zero knowledge schemes do not exploit social information. On the other hand, non-zero knowledge schemes employ social information about node behaviors or social relationships for forwarding decisions in OPPNETs.

In zero knowledge schemes, CSROR [10] finds the optimum values of the bandwidth, battery power, and threat level to implement route discovery. Epidemic [11] distributes messages to each of them when each node meets other nodes, creating replicas of the messages. In Spray-and-Wait [12], a node "sprays a number of copies into" some nodes in the network and then "waits" until one of these nodes meets the destination. Ticket-based broadcasting [13] exploits the number of tickets associated with each packet and determines a packet's priority. Homing spread [14] creates extra delivery overhead for mobile nodes because it spreads messages to the detected communities via the relay nodes. HFS [15] floods messages only to nodes in hotspots where nodes often meet each other.

Non-zero knowledge schemes can be further categorized into three schemes: centrality/similarity-based, social context-based, and probability-based. The centrality/similarity-based schemes include SimBet [16], Bubble Rap [17], and SANE [18]. In SimBet, when each node meets other nodes, it provides a message to the other nodes with betweenness centrality and similarity utility values until the destination node is encountered. In Bubble Rap, a message is sent to the destination node or its community by both global and local centralities. Note that SANE utilizes both user interests and their similarity.

The social context-based schemes include Label [19] and HiBop [20]. Label selects some nodes to directly forward messages to the destination or to the next-hop node belonging to the same label as that of the destination. HiBop requires personal information, such as residence, employer, and hobbies, as well as the system information.

Finally, the probability-based schemes include ProPhet [21], PeopleRank [22], and MobySpace [23]. ProPhet estimates the delivery predictability for forwarding decision, $P(a, b)$, which indicates how likely node b is to receive a message from node a during the warm-up period. PeopleRank adopts Google's PageRank algorithm for forwarding decisions. MobySpace exploits the knowledge about a node's interest and mobility information, such as the coordinates and locations.

Most non-zero knowledge schemes require global information for forwarding decisions. Therefore, these schemes take advantage of real datasets for their simulations. These datasets can be preprocessed in advance because they contain information on mobility, contact trace, and social interaction graphs. Unfortunately, such preprocessing on real datasets results in the loss of generality.

3. SIMPLIFIED OPPNET MODEL

3.1 Network Graph

We model an OPPNET as an undirected graph, $G = <V, E>$. Vertex set V and edge set E consist of all nodes and all links between nodes, respectively. The weight of an edge indicates a utility value in the proposed scheme.

3.2 Network Model

Each node in our OPPNET has a unique identifier. The nodes are denoted by $N = \{N_1, N_2, N_3, \ldots, N_m\}$, where m is the number of nodes in the network. The set of encountered nodes of node N_i is denoted by S_i. For simplicity, we do not consider resources such as buffer, bandwidth, and power. In addition, because the focus of this paper is not on reduction of computational costs, we do not consider it.

3.3 Mobility Model

We use HCMM as the node mobility model in this paper. It is a widely used model for the spatial and temporal properties of human mobility in social information. HCMM more practically reflects human behaviors. Each node selects the destination using the social weights of the nodes; therefore, a strong social weight implies a high probability to travel to a specific community. The distance between a pair of communities additionally affects the probability to visit. Accordingly, each node belongs to a community. The community within which a node is initially located is called the node's home community. Each node frequently visits its home community and infrequently visits other communities. We assume that each node knows whether other nodes belong to its home community. Nodes lack global information except for node identifiers. In addition, each node has a label [19] that indicates its home community index, denoted by $H = \{H_1, H_2, H_3, \ldots, H_r\}$, where r is the number of communities. Each node is aware of its own speed and current location. A node can periodically measure its location. To determine its speed and location, each node is assumed to have positioning system equipment.

4. PROPOSED SCHEME

4.1 Overview

The proposed scheme obeys the rules of typical message forwarding: each node forwards a message to the destination via relay nodes. Unlike forwarding in MANETs, nodes do not maintain a routing table for forwarding because there may be no stable route between the source and destinations. Thus, it is important to select proper relay nodes for successful delivery of the message within a reasonable delay. We exploit contact probability to the destination and betweenness centrality for forwarding. During the warm-up period, each node updates and exchanges its contact probability and betweenness centrality upon contact with one another node. After that, each node issues a message. The network has no infrastructure for global information; therefore, it might be difficult for a node to know the contact probabilities and betweenness centralities of the other nodes in range, which dynamically change. Accordingly, each node updates and exchanges its information, including contact probability and betweenness centrality, with each node it encounters. The source node forwards the message to an encountered node only if that node has a higher competency for delivering the message than the source node does. Message forwarding is terminated when the message is delivered to the destination. Fig. 1 shows an overview of RCPB. Note that small white circles indicate nodes, and white nodes in a large circle have higher contact probabilities for a certain node, indicating that they tend to gather together. In RCPB, nodes with higher betweenness centralities compensate for the intermittent connection disruptions among the nodes in the network by combining contact probabilities with betweenness centralities, which enhances the performance in terms of both delivery ratio and network traffic. A method of calculating the contact probability and betweenness centrality of a node for forwarding is described below.

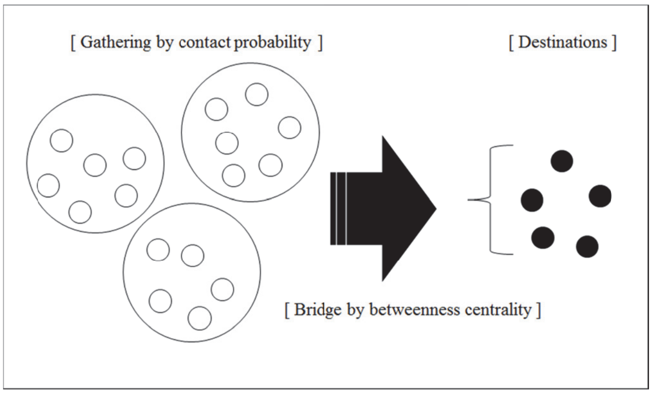


Fig. 1. Overview of RCPB.

4.2 Contact Probability

Contact probability is an important factor for forwarding a message to the destination. A node with a high contact probability with respect to the destination is likely to forward a message to the destination. We consider the frequency, longevity, and regularity of nodes' contacts [24] to refine contact probability; these metrics present the frequency, duration, and regularity with which each node meets other nodes, respectively. We incorporate these metrics using the following equation, for which we assume exponential inter-contact time.

$$P(i,j) = 1 - \exp\left(-\frac{\frac{1}{c_{ij}}\sum u(i,j)}{\frac{1}{c_{ij}}\sum I(i,j)}\right), \tag{1}$$

where $P(i, j)$ indicates the contact probability of N_i and N_j, C_{ij} represents the total contact counts of N_i and N_j, $U(i, j)$ is the contact duration of N_i and N_j, and $I(i, j)$ is the inter-contact time between N_i and N_j. Note that the total contact count is how many other nodes each node meets, the contact duration is the time period when two nodes meet, and the inter-contact time is the time gap between when two node contact and when the same two nodes contact again [1]. In Eq. (1), the contact probability of two nodes is estimated under the assumption of exponential inter-contact time [12]. Note that the calculation of $P(i, j)$ itself does not rely on the assumption of exponential inter-contact times. Using a particular estimation that is more realistic for a network should result in better forwarding performance [25].

The sums of both the contact duration and inter-contact time between N_i and N_j is divided by the total contact counts (C_{ij}) to obtain the average value. Note that $P(i, j)$ increases as the average contact duration increases, whereas $P(i, j)$ increases as the average inter-contact time decreases. The average values of both contact duration and inter-contact time in Eq. (1) capture regularity.

If a lengthy period has elapsed since N_i and N_j have encountered each other, their contact probability must be modified with aging factor γ in terms of time t as

$$P(i,j) = \left[1 - \exp\left(-\frac{\frac{1}{c_{ij}}\sum U(i,j)}{\frac{1}{c_{ij}}\sum I(i,j)}\right)\right] \times \gamma^t, \tag{2}$$

where t is the time that has elapsed since their last encounter. In addition, the contact probability must incorporate the transitivity property; that is, when N_i meets N_j after N_j encounters N_k, N_i updates $P(i, k)$ according to $P(i, j)$ and $P(j, k)$ as

$$P(i, k) = 1 - (1 - P(i, j)) \times (1 - P(i, k)). \tag{3}$$

Note that N_i does not update $P(i, k)$ if N_i had previously encountered N_k because $P(i, k)$ was already updated at that time. We can now use contact probability $P(i, j)$, along with betweenness centrality, for forwarding messages.

4.3 Centrality

Centrality has structural importance in social network analysis. There are several ways to measure it; we use the most popular metrics, such as degree, betweenness, and closeness centralities [26-28].

Degree centrality indicates the number of nodes (*i.e.*, ties) connected to a node. As a node's degree centrality increases, so does its chance of contacting other nodes in a network. The degree centrality of N_i is calculated as

$$Degree_i = \sum_{j=1}^{m} l(i,j), \tag{4}$$

where $l(i, j) = 1$ if a link exists between N_i and N_j, and m is the number of nodes. In this paper, the degree centrality of N_i is denoted by $|S_i|$, which means the number of nodes N_i encountered.

Closeness centrality denotes how close a node is to all other reachable nodes in the network. It can be regarded as a measure of the time it will take information to spread from a given node to each of the other nodes in the network. The closeness centrality of N_i is calculated as

$$Closeness_i = \frac{m-1}{\sum_{j=1}^{m} d(i,j)}, \tag{5}$$

where $d(i, j)$ is the geodesic distance between N_i and N_j. It is difficult to measure closeness centrality in an OPPNET because nodes require complete knowledge of the network topology. Instead, we enable nodes to calculate closeness centrality by the Euclidean distance with x-y coordinates obtained from their positioning systems. Whenever they meet one another, they update their coordinates, both their own and those of their encountered nodes.

Finally, betweenness centrality indicates the number of shortest paths from all nodes to all others that pass through a node. A node with a high betweenness centrality can enhance interactions between the nodes that it links [28]. Betweenness centrality for N_i is calculated as

$$B(i) = \sum_{j=1}^{m} \sum_{k=1}^{j-1} \frac{g_{ik}(i)}{g_{jk}}, \tag{6}$$

where g_{jk} is the total number of geodesic paths between N_j and N_k, and $g_{ik}(i)$ is the number of those geodesic paths that include N_i. Determining the betweenness centrality of a node is also difficult on account of the lack of a global network topology. Hence, we measure it with the equation used in the ego betweenness [29]:

$$A^2[1-A], \tag{7}$$

where A is the adjacency matrix of N_i. $A_{ij} = 1$ if there is contact between N_i and N_j, and 0 if there is not. Fig. 2 shows an example of the calculation of the betweenness centrality $B(1)$ for N_1, assuming that N_1 has encountered N_2, while N_3 had encountered N_1, N_2, and N_4, and N_1 had earlier encountered N_4 and N_5. When $i \neq j$, since the walk is of length 2, it must be a path. The number of paths of length 2 is needed to count for non-adjacent pairs of nodes since these will be geodesics. It follows that $A^2[1-A]_{i,j}$, where 1 is a matrix of all 1's, gives the number of geodesics of length 2 joining i to j. The sum of the reciprocal of the entries gives the ego betweenness (this has to be halved if it is a graph).

$A =$

	N_1	N_2	N_3	N_4	N_5
N_1	0	1	1	1	1
N_2	1	0	1	0	0
N_3	1	1	0	1	0
N_4	1	0	1	0	0
N_5	1	0	0	0	0

$A^2[1-A] =$

	N_1	N_2	N_3	N_4	N_5
N_1	*	*	*	*	*
N_2	*	*	*	2	1
N_3	*	*	*	*	1
N_4	*	*	*	*	1
N_5	*	*	*	*	*

Fig. 2. Calculation of the betweenness centrality of N_1.

Since the matrix is symmetric we need only consider the zero entries above the leading diagonal. Consequently, the ego betweenness is simply the sum of the reciprocals of the entries; $B(1)$ is 1/2 + 1/1 + 1/1 + 1/1 = 3.5 as shown in [29]. RCPB exploits betweenness centrality as well as contact probability for forwarding.

4.4 Integration of Contact Probability and Betweenness Centrality

We now integrate the contact probability and betweenness centrality to determine a value for forwarding. Let us assume that N_d is the destination, N_i holds the message to N_d, and N_i just encounters N_j. Because $P(i, j)$ is the probability that N_i will meet N_j, and $B(i)$ indicates how structurally central N_i is in the network topology, we define $F_i(d)$ of N_i as

$$F_j(d) = P(i, d) \times B(i), \tag{8}$$

In Eq. (8), the contact probability is multiplied by the betweenness centrality because the contact probability varies from 0 to 1.0 and the betweenness centrality is non-negative. Whenever N_i meets N_j, N_i calculates $F_i(d)$ and sends the message to N_j when $F_j(d)$ is larger than $F_i(d)$. Hence, a node forwards the message to other nodes that are likely to be close to the destination.

4.5 Forwarding in RCPB

Each node N_i maintains the information entry $< ID_i, B(i), A_i, F_i, P_i, I_i, U_i >$ to update the contact probability and betweenness centrality, where ID_i is the ID of N_i, A_i is the adjacency matrix of N_i, $F_i = \{F_i(1), F_i(2), \ldots, F_i(m), F_2(i), F_3(i), \ldots F_m(i)\}$, $P_i = \{P(i, 1), P(i, 2), \ldots, P(i, m), P(2, i), P(3, i), \ldots P(m, i)$, $I_i = \{I(i, 1), I(i, 2), I(i, 3), \ldots I(i, m)\}$, and $U_i = \{U(i, 1), U(i, 2), U(i, 3), \ldots, U(i, m)\}$. When N_i meets N_j, $F_i(j)$ is calculated with $B(i)$ and $P(i, j)$. N_i additionally computes $F_j(i)$ at the same time to reduce extra communication between them.

The RCPB forwarding algorithm is outlined in Algorithm 1. Assume that N_i has a message destined for N_d. When N_i encounters N_j, N_i exchanges A_i, F_i, and P_i with N_j. N_i then updates contact probability $P(i, j)$ with $I(i, j)$ and $U(i, j)$. Additionally, N_i updates each $P(i, k)$ for $k \neq i \neq j$ in P_i using Eq. (3) with P_j; moreover, it updates betweenness centrality $B(i)$ by combining A_i with A_j using Eq. (7). Next, N_i computes $F_i(d)$ and $F_j(d)$ using Eq. (8). Finally, N_i compares $F_i(d)$ with $F_j(d)$. If $F_j(d)$ is greater than $F_i(d)$, N_i forwards the message to N_j.

Algorithm 1: Pseudo code for RCPB forwarding

```
//After discovery of encountered node Nj
RCPB_Forwarding {
Exchange_information (Ni, Nj); //Exchange Ai, Fi, and Pi with those of Nj
Update_ContactProbability(Pi); //Update the contact probabilities
Update_Betweenness(B(i)); //Update the betweenness centrality of Ni by combining Ai
                                   with Aj
Calculation_FValue(Fi(d), Fj(d));// Calculate Fi(d) and Fj(d)
If Nj = Nd
Forward the message to Nj;
Else If Fi(d) < Fj(d)
Forward the message to Nj;}
```

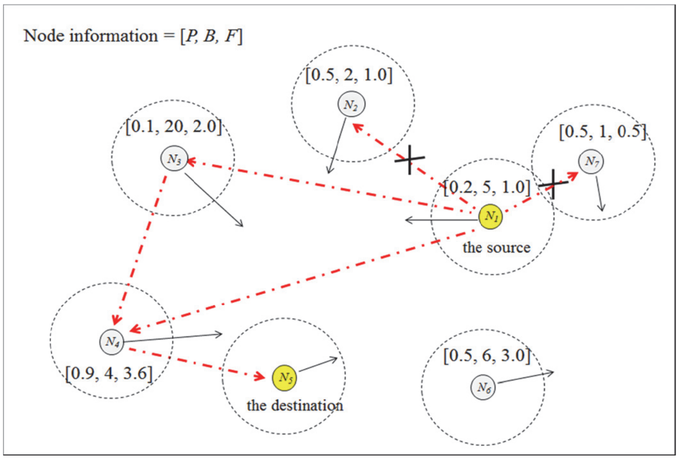


Fig. 3. Example of RCPB forwarding.

Fig. 3 shows a message forwarding example in RCPB. Each node includes information, such as contact probability P for the destination, betweenness centrality B, and forwarding value F. Each node moves according to its solid arrow. Source node N_1 has the message for destination node N_5. In Fig. 3, N_1 encounters nodes N_7, N_2, N_3, and N_4; in turn, N_1 respectively sends the message to both N_3 and N_4 because the F values of N_3 and N_4 are 2.0 and 3.6, respectively, which are larger than N_1's F value, 1.0. Although N_6 has a higher F value, 3.0, than N_1, N_1 cannot send the message to N_6 because they do not connect with each other, as shown in the figure. When N_3 meets N_4, if N_4 has already received the message, N_3 does not forward it. Finally, when N_3 or N_4 meets N_5, it sends the message to N_5.

5. EXPERIMENTAL RESULTS

5.1 Simulation Environment

We used the network simulator, NS-2 v2.35 [30] and the mobility model of the OPPNET simulations, HCMM [7] for our simulation environments. Compared with HCMM, real datasets include mobility and contact trace as well as a social interaction graph. The social information contains very strong properties like declared friendships, common interests and affiliations [31]. However, a suitable dataset for the performance of a scheme at specific time can be extracted from the real datasets and additional information such as profile, interest, and social context can be used as input to their advantages. Such input manipulations result in the loss of generality. Even [31] analyzes that the performance of forwarding schemes using real datasets relies on the input data. Since HCMM does not have contact information, we need a warm-up period to obtain social information to simulate the social-aware forwarding schemes. In HCMM we are not allowed to manipulate the input data to our advantages. We thus use the HCMM model which is a widely used mobility pattern for the simulations.

The entire network area and community size were set to 450×450m, and 150×150m, respectively. The number of communities was four among nine grids, and each community had ten or more nodes. The number of nodes was set to 40, 50, 60, and 70. The communication range varied from 10 to 50m. Because HCMM does not include contact information, a warm-up period was required to obtain and update the contact information, including contact probability and centrality, to simulate the forwarding schemes. The warm-up period was 1,000s. The velocity of the node range varied from 1 to 9m/s, which was appropriate for either people or vehicles. In our simulator, each node issued one message with randomly selected destinations. After a source node sent the message to the other nodes, it did not delete the message. Aging factor γ was set to 0.98. The total simulation time was 8,000s. We ran each scheme 20 times to determine the average results. Table 1 summarizes the parameters used in our simulation. Our simulation environments followed [15].

Table 1. Parameters for the simulation.

Parameter	Value (Default)
Network area	$450\times450\text{m}^2$
Community size	$150\times150\text{m}^2$
Number of grids	9
Number of communities	4
Number of nodes	40, 50, 60, 70, (40)
Communication range	10, 20, 30, 40, 50, (10)m
Velocity of nodes	1~9m/s
Aging factor γ	0.98
Warm-up period	1,000s
Simulation time	8,000s

We evaluated the proposed scheme with the following performance metrics:

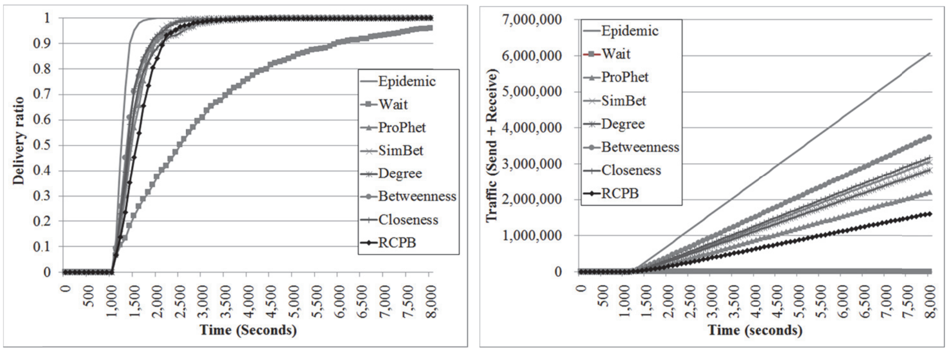
1) Delivery ratio: The ratio of the number of delivered messages to the total number of messages issued.
2) Network tra ffic: The total number of messages sent and received.
3) Delay: The time required for a message to travel from the source to the destination.
4) Hop count: The average number of hops required for a message to travel from the source to the destination.

We simulated and compared RCPB with various forwarding schemes such as Epidemic, Wait, ProPhet, SimBet, and pure centrality-based schemes. All the schemes, except Wait, achieved a 1.0 delivery ratio.

5.3 Simulation Results

5.3.1 Effect of the simulation time

Figs. 4 (a) and (b) show the delivery ratios and network traffic, respectively, as the simulation time reached 8,000s. The results are shown after 1,000s, including the warm-up period. The number of nodes and the communication range were set to 40 and 10m, respectively. As shown in Fig. 4 (a), the delivery ratio of each scheme increased as the simulation time passed on account of the delivery of messages. Most schemes achieved a maximum delivery ratio faster than that of Wait because they are multi-copy schemes and they distributed the messages. Because Wait does not allow multiple copies of messages and waits for the message to encounter the destination, it required a much longer time to reach the 1.0 delivery ratio. RCPB reached the 1.0 delivery ratio, which was slightly slower than that of the other schemes (except Wait), because it distributed only a few copies of messages to the nodes with higher F values by considering both the contact probability and betweenness centrality. As shown in Fig. 4 (b), each scheme suffered from higher network traffic as the time passed. However, RCPB showed much lower traffic than the other schemes except Wait. Because RCPB considered not only the betweenness centrality of a node, but also the frequency, longevity, and regularity for the contact probability, it distributed the messages to a smaller number of proper relay nodes for the destination compared to ProPhet, which used only a simple contact probability, and SimBet, which used similarity and betweenness centrality. In addition, RCPB filtered out nodes that had not met the destination for a long time with the aging factor. As a result, RCPB handpicked the structurally important nodes as well as the nodes recently closer to the destination. Thus, RCPB distributed the messages to only those key nodes and could thereby reduce network traffic.

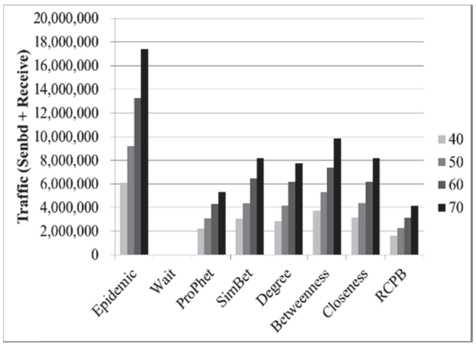


(a) Delivery ratio. (b) Network traffic.

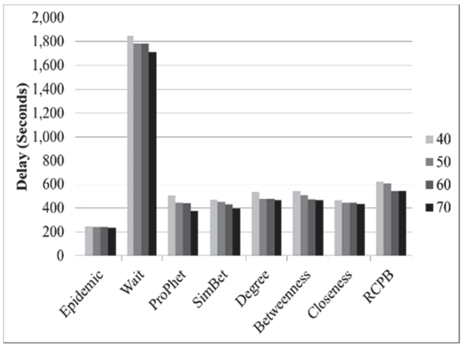
Fig. 4. Effect of the simulation time.

5.3.1 Effect of the number of nodes

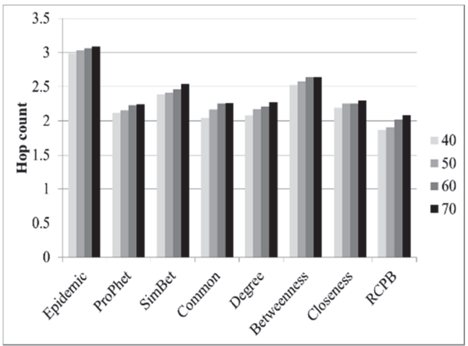
We examine the performance as the number of nodes increased. Fig. 5 (a) shows the network traffic when the number of nodes increased. As expected, the traffic amounts of most schemes enormously increased with the number of nodes. In particular, the gap between RCPB and each of the other multi-copy schemes was large. RCPB had the lowest traffic except for Wait. In RCPB, as the number of nodes increased, each node could more accurately calculate the betweenness centrality because larger and denser components appeared in the network. Hence, RCPB could select more structurally important nodes for forwarding. Fig. 5 (b) shows the transmission delay. The delays of most schemes decreased as the number of nodes increased; Wait showed similar patterns regardless of the number of nodes because it did not distribute multiple copies. The delay in RCPB was somewhat longer than with the other schemes because the latter schemes sent more copies. Fig. 5 (c) shows the hop counts of the schemes. Wait did nothing until each destination was encountered; hence, it had a hop count of one. Basically, as the number of nodes increased, the hop counts of all schemes likewise increased. However, RCPB had a smaller hop count than the other schemes because it distributed the messages to nodes that were both structurally important and recently closer to the destination.



(a) Network traffic.



(b) Transmission delay.

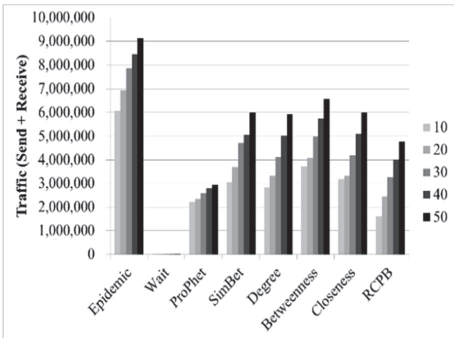


(c) Hop count.

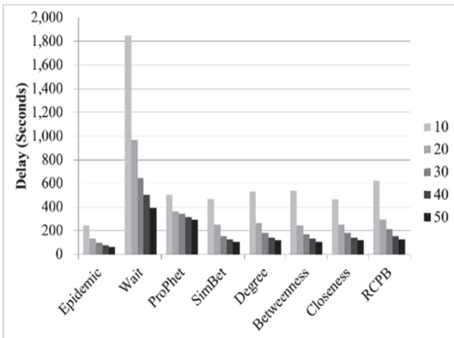
Fig. 5. Effect of the number of nodes.

5.3.3 Effect of the communication range

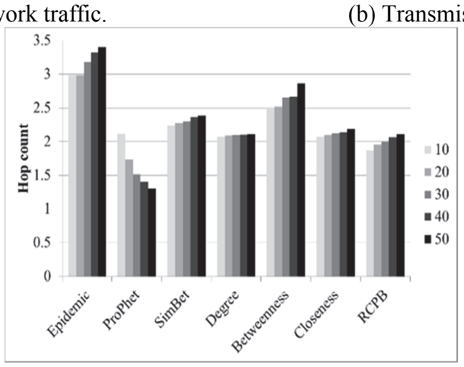
Finally, we compare the effect of the nodes' communication ranges for each scheme. As shown in Fig. 6 (a), as the communication range became wider, all the schemes except Wait increased network traffic. Interestingly, ProPhet showed a moderate increase because only the nodes with a higher contact probability to the destination participated in the delivery of messages within their communication range. RCPB showed the smallest traffic except for ProPhet and Wait. Because RCPB considered both contact probability and betweenness centrality, it had higher traffic than ProPhet but less than the others. Fig. 6 (b) shows the transmission delays of the schemes. Most schemes naturally incurred shorter delays as the communication ranges became wider. Epidemic showed the smallest delay, as expected. Most schemes except ProPhet and Wait exhibited similar results. ProPhet suffered from a longer delay than RCPB, except when the communication range



(a) Network traffic.



(b) Transmission delay.



(c) Hop count.

Fig. 6. Effect from the communication range.

was 10 and 20 m. In RCPB, as the communication range became wider, each node was likely to more frequently meet other nodes with a longer duration. When the communication range was longer than 20 m, the RCPB delay significantly decreased because RCPB could consider a larger number of nodes with higher frequency and longevity. Fig. 6 (c) shows the hop counts of the schemes. As the communication range became wider, all the schemes except ProPhet increased their hop counts. The hop count of ProPhet decreased as the communication range became wider because only the nodes with higher contact probability to the destination participated in forwarding. We expected RCPB's hop count to decrease; instead, it showed a moderate increase because it was additionally affected by betweenness centrality. Nonetheless, RCPB had an overall small hop count. The results in all figures demonstrate that RCPB maintains a well-balanced performance that minimizes both network traffic and transmission delay.

6. CONCLUSION

Existing forwarding schemes that consider either contact probability or betweenness centrality suffer from higher network traffic and fail to balance network traffic and transmission delay while maintaining a lower hop count. In this paper, we proposed an effective forwarding scheme, RCPB, which considers both contact probability and betweenness centrality. RCPB incorporates the frequency, longevity, and regularity of node contact to compute a more effective contact probability for forwarding. Nodes with the contact probabilities to other nodes tend to gather together. This scheme additionally enables nodes with higher betweenness centrality to compensate for the intermittent disruptions of connections among nodes in the network. RCPB thus distributes messages to a proper number of nodes that have recently been closer to the destination and are structurally important connections with other nodes for forwarding. Consequently, RCPB reduces network traffic and lowers hop count while maintaining an acceptable transmission delay. Hence, RCPB is a well-balanced forwarding scheme for OPPNETs. In the future, we will consider more elaborated integration and other metrics for network analysis in forwarding, such as selfishness and similarity.

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