Buffer Scheme Optimization of Epidemic Routing in Delay Tolerant Networks

Jian Shen, Sangman Moh, Ilyong Chung, and Xingming Sun

Abstract: **In delay tolerant networks (DTNs), delay is inevitable; thus, making better use of buffer space to maximize the packet delivery rate is more important than delay reduction. In DTNs, epidemic routing is a well-known routing protocol. However, epidemic routing is very sensitive to buffer size. Once the buffer size in nodes is insufficient, the performance of epidemic routing will be drastically reduced. In this paper, we propose a buffer scheme to optimize the performance of epidemic routing on the basis of the Lagrangian and dual problem models. By using the proposed optimal buffer scheme, the packet delivery rate in epidemic routing is considerably improved. Our simulation results show that epidemic routing with the proposed optimal buffer scheme outperforms the original epidemic routing in terms of packet delivery rate and average end-to-end delay. It is worth noting that the improved epidemic routing needs much less buffer size compared to that of the original epidemic routing for ensuring the same packet delivery rate. In particular, even though the buffer size is very small (e.g., 50), the packet delivery rate in epidemic routing with the proposed optimal buffer scheme is still 95.8%, which can satisfy general communication demand.**

Index Terms: **Buffer scheme, delay tolerant network, dual problem, epidemic routing, optimization.**

I. INTRODUCTION

Delay tolerant networks (DTNs) are a practical class of emerging wireless networks, which are occasionally connected networks comprised of one or more protocol families and experience frequent and long-duration partitions as well as long delays [1]. The traditional view of a network as a connected graph over which end-to-end paths need to be established might not be appropriate for modeling existing and emerging wireless networks. Due to the wireless propagation phenomena, node mobility, low power nodes periodically shutting down, etc., connectivity in many wireless networks is intermittent [2]. Because end-to-end connectivity in DTNs cannot be guaranteed, the routing protocols that have good performance in the conventional networks are not suitable for DTNs. To enable some services to operate even under these challenging conditions, the store-carry-and-forward protocols are proposed, where a node may store a message in its buffer and carry it along for long periods of time until the node can forward it further. This routing may happen randomly, which is usually based on statistical information [3] or even other relevant information about the destination (e.g., social links, affiliation, etc.). Furthermore, due to the inherent uncertainty caused by the lack of complete information about other nodes on the network, many replicas of the same message may be propagated to increase the probability of successful delivery.

Several routing protocols in DTNs have been studied in [4]–[20]. Among them, the first and most popular routing protocol in DTNs is epidemic routing [4], which disseminates a message replica to every node on the network. Epidemic routing uses the simplest policy called first-in-first-out (FIFO) as its buffer scheme. This scheme is simple to implement and bounds the amount of time that a particular message is likely to remain “live”. Once enough new messages have been introduced into the system, old messages are likely to be flushed from the buffer. FIFO is a very reasonable policy as long as the buffer size on the host is larger than the expected number of messages in transit at any given time. However, if the number of messages in transit exceeds the buffer size, then the performance of epidemic routing will fall down hastily. It has been demonstrated that buffer constraints can severely affect the relative and absolute performance of epidemic routing and, in consequence, applications. A number of studies have clearly shown that epidemic routing can obtain maximum delivery rate and minimum delivery delay without buffer constraints, but performs poorly when the size of buffers is limited [21], [22].

Recently, many studies have focused on designing new routing protocols to satisfy general communication demand under the extreme challenging environment in DTNs. In their research papers [4]–[17], the authors claim that their protocols are excellent in comparison with the well-known epidemic routing in terms of packet delivery rate, normalized routing overhead, average end-to-end delay, and so on. However, few of them have attempted to improve the performance of the original epidemic routing by optimizing the buffer scheme. As we know, epidemic

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routing can be simply implemented in the real DTNs' applications due to its advantage of simple epidemic message dissemination. However, the performance of epidemic routing cannot be guaranteed, especially under the condition of fixed buffer size in a node. Hence, optimizing the buffer scheme of epidemic routing to improve performance will be very practical and valuable.

In this paper, we propose an optimized buffer scheme of epidemic routing on the basis of the Lagrangian and dual problem models. We consider that the best choice of the message to be dropped is strongly dependent on the number of copies of the different messages existing in the buffer of a node on the network. None of the previous buffer schemes take this network-wide statistics into account. In addition, in order to optimize the buffer scheme in epidemic routing to maximize the average delivery rate, we take into account the information that is relevant to encounter-based message dissemination [23]. Our simulation results show that epidemic routing via the proposed optimal buffer scheme outperforms the original epidemic routing in terms of packet delivery rate and average end-to-end delay. Moreover, the improved epidemic routing needs much less buffer size compared to that of the original epidemic routing for ensuring the same packet delivery rate. Consequently, the proposed optimal buffer scheme makes the improved epidemic routing very practical and valuable. In addition, the proposed optimal buffer scheme improves epidemic routing in DTNs to satisfy general communication demand.

The rest of this paper is organized as follows: In the following section, related works are briefly reviewed. The optimal buffer scheme in epidemic routing is presented in detail in Section III. The simulation and results are discussed in Section IV. Finally, we conclude this paper in Section V.

II. RELATED WORKS

Epidemic routing [4], as the name suggests, likes the pattern of pandemic virus transmitting. In epidemic routing, all nodes can become a carrier, which can take the message from one node to another. In this way, messages are quickly distributed through the networks due to node random mobility. Moreover, epidemic routing relies upon carriers coming into contact with one another in the network through node mobility. We give an example as depicted in Fig. 1 to simply explain the process of epidemic routing, where anti-entropy [4] sessions guarantee the eventually delivery of messages to the destination given sufficient buffer space and time. In epidemic routing, the critical resource is the buffer. A node with large buffer size has enough space to store lots of messages such that it can carry these messages along for long periods of time until the appropriate forwarding opportunities become available. Once the buffer size becomes insufficient in the nodes, the epidemic routing performance will fall down hastily. Hence, epidemic routing is very sensitive to the size of buffer and can only achieve good performance with large buffer size. Note that epidemic routing uses the simplest policy called FIFO as its buffer scheme.

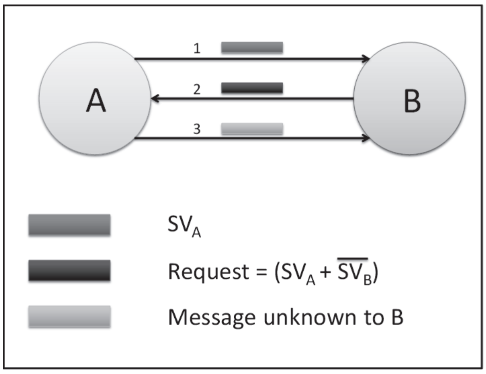

Fig. 1. The process of epidemic routing protocol.

Some buffer management schemes have been studied in [23]–[25], such as Drop Tail, Drop Oldest, and Drop Youngest. However, these buffer schemes are not suitable for the extreme challenging environment of DTNs and they cannot take into account information relevant to encounter-based (or store-carry-and-forward) message delivery. Recently, an intelligent buffer management scheme in location and direction aware priority routing (LDPR) has been proposed in [11], which takes advantage of the nodes' information of the location and moving direction to store messages into buffer space. In [11], a node can obtain its location and moving direction information by periodically receiving beacon packets from anchor nodes and referring to received signal strength indicator (RSSI) for the beacon. Each message, in addition, is assigned a certain priority according to the message attributes (e.g., importance, validity, security, and so on). The message priority determines the dropping sequence when the buffer is full. However, the communication overhead for comparing the location and moving direction information is high.

In [22], Zhang *et al.* develop a rigorous, unified framework based on ordinary differential equations (ODEs) to study epidemic routing and its variations. They present an analysis of buffer-constrained epidemic routing, and evaluate some of the simple buffer management policies. In addition, Zhang *et al.* conclude that giving priority to source messages improves the delivery rate. Note that the main purpose of [22] is to show how ODE models can be advantageously employed to study the performance of various epidemic style routing schemes, rather than to provide final conclusions about the merits of specific schemes. Later, [26] and [27] present some methods to optimize the performance of epidemic routing; however, [26] performs only a preliminary evaluation and [27] optimizes the delivery rate by introducing a new forwarding policy named transmit smallest message first (TSMF), which is based on message size rather than buffer size.

Recently, Krifa *et al.* [2] propose an efficient buffer scheme based on global knowledge. In order to maximize the average delivery rate and minimize the average delivery delay, global information about the network needs to be obtained. Krifa *et al.* introduce a learning process that permits a DTN node to gather knowledge about the global network state history by making in-band exchanges with other nodes. However, Krifa *et al.*'s method is not feasible in practice due to intermittent network connectivity and the long time it takes to update the list of encountered nodes.

In this paper, we design an optimal buffer scheme for epidemic routing. We assume that a node should not discard its own valid messages (called source messages) to create places in its buffer to accommodate new messages forwarded by other nodes. This assumption ensures that at least one copy of each message stays in the network as long as its time-to-live (TTL) does not expire. If all buffered messages are source ones and the arriving message is also a source message, then we choose to delete the oldest one. In this case, we give the oldest source message the lowest priority.

III. OPTIMAL BUFFER SCHEME IN EPIDEMIC ROUTING

A buffer scheme defines which message should be dropped when the buffer of a node is full and a new message is to be accommodated. We assume that B is the total messages in the buffer of a node. Each message (message i) in the buffer has a set of information S_i stored with it. Note here that S_i can include the source ID, time when the message was generated, TTL value, and so on. In the DTN architecture, the TTL value is a timeout value, which specifies when a message is no longer useful and should be deleted. Let a new message arrive at a buffer that is full. Then, usually, a buffer scheme is a function $f(S_1, S_2, \cdots, S_B, S_{\text{new}}) = j \in \{[1, B] \cup [\text{new}]\}$, which determines on message j should be dropped among the messages already in the buffer and the new message. This buffer scheme is based on the information of all messages in the buffer. Note here that we use the Lagrangian and dual problem models to calculate the global information so as to optimize the buffer scheme. First, we will describe the definition of the problem and formulate the Primal Problem. Then, we will present the dual problem from the Lagrangian function. Finally, we will solve the dual problem to obtain the optimal solution. According to the optimal solution, we can get the optimal buffer scheme in epidemic routing. Applying Lagrangian and dual problem models can make the calculation of the global information easier and more practical, compared with the statistical learning process in [2].

A. Problem Definition

We suppose that L is the total number of nodes on the network. All nodes have the same transmission range. Each node has a buffer, where it can store up to B messages in transit. The messages stored in the buffer of a node are either received from other nodes or generated by it. Each message is destined to one of the nodes in the network, and has a TTL value. After the TTL value is elapsed, the message is no longer useful to the application and should be dropped by its source node and all intermediate nodes. The message can also be dropped when delivery is successful.

In the context of DTNs, message transmissions in epidemic routing occur only when the nodes encounter each other. The minimum time a node has to wait until it can further forward a message is the time until it encounters another node that can act as a relay. Thus, the time elapsed between nodes meeting is the basic delay component. This inter-encounter time between nodes depends on the value of a particular property of the assumed mobility model, namely the meeting time [29]. In this paper, we choose the most popular model-Random Waypoint as our mobility model, which will be described again in Section IV. In addition, we consider that bandwidth is not an issue. Hence, when two nodes meet, there is enough time to exchange their messages. Messages are not fragmented and are transmitted from one node to another during a contact.

Next, we define the meaning of meeting time, which is the same as the definition in [2]. Let nodes i and j move according to some mobility process, and let them start from their stationary position at time 0. Moreover, let $X_i(t)$ and $X_j(t)$ indicate the mobility process (position) of nodes i and j at time t, respectively. The meeting time (U) between nodes i and j is defined as follows: $U = \min\{t\colon \parallel X_i(t) - X_j(t) \parallel \leq \beta\}$, where β is the transmission range of each node and $\parallel X_i(t) - X_j(t) \parallel$ implies the Euclidean distance between the positions of nodes i and j. Note here that the meeting time (U) represents the time when the two nodes first come within the transmission range (β) of each other. In this paper, we assume that the meeting time of mobility model is exponentially distributed [2] or has at least an exponential tail with parameter $\lambda = 1/(E[U])$, where $E[X]$ denotes the expectation of a random variable X. It has been shown that many popular mobility models like Random Walk [30], Random Waypoint, and Random Direction [23], as well as other more sophisticated synthetic models like the community model in [23] have such a property. Hence, we use the exponential meeting time in our mobility model.

The proposed optimal buffer scheme in epidemic routing determines which message should be dropped when a node's buffer is full and a new message has arrived. The major objective of our optimal buffer scheme is maximizing the average delivery rate. From the simulation results, we can see that the optimal buffer scheme can also minimize the average delivery delay, which dramatically improves the performance of epidemic routing and makes the improved epidemic routing very practical and valuable. We summarize the notations used in this paper in Table 1.

In epidemic routing, messages are propagated in the network using replication, each of which has a finite TTL value. The source of the message keeps a copy of it during the whole TTL duration, while intermediate nodes are not obliged to do so. At a certain time instant, a new message copy arrives at a new node's buffer during an encounter when the node's buffer is full. Suppose that we know all the messages in the network and the number of copies of each message at that time instant; the problem we would like to solve is: What is the best message to be dropped among the ones already in the buffer of the given node and newly arrived one in order to maximize the average delivery rate of all messages in the network? Let us suppose that there are K messages in the network at a certain time t. For message $i \in [1, K]$ with the elapsed time T_i, let $m_i(T_i)$ and $n_i(T_i)$ be the number of nodes that have "seen" the message since its creation (excluding the source node) and those who have a copy of the message at this instant ($n_i(T_i) \leq m_i(T_i) + 1$). Note here that node A has "seen" message i when A had received a copy of message i sometime in the past, regardless of whether A still has the copy or has already removed it from its buffer. According to the theorem in [2], the optimal buffer scheme in epidemic routing that maximizes the average delivery rate is to drop the message i satisfying:

Table 1. Notation used in this paper.

Variable	Description
L	Number of nodes in the network
$K(t)$	Number of distinct messages in the network at time t
TTL_i	Initial TTL value for message i
R_i	Remaining TTL for message i
$T_i = TTL_i - R_i$	Elapsed time for message i. It measures elapsed time since message i was generated by its source.
$n_i(T_i)$	Number of copies of message i in the network after elapsed time T_i
$m_i(T_i)$	Number of nodes (excluding the source node) that have seen message i since its creation until elapsed time T_i
λ	Meeting rate between two nodes, $\lambda = 1/(E[U])$ where $(E[U])$ is the average meeting time

$$i = \min\left[\left(1 - \frac{m_i(T_i)}{L-1}\right)\lambda R_i e^{-\lambda n_i(T_i) R_i}\right]. \tag{1}$$

Hence, we can easily define the Primal Problem as follows.

Primal Problem:

$$\begin{aligned}
\textbf{min} \quad & \left(1 - \frac{m_i(T_i)}{L-1}\right)\lambda R_i e^{-\lambda n_i(T_i) R_i} \\
\textbf{Subject to:} \quad & n_i(T_i) \leq m_i(T_i) + 1 \\
& n_i(T_i) \leq L \\
& m_i(T_i) \leq L - 1 \\
& T_i \leq TTL_i
\end{aligned}$$

B. Dual Problem

From the Primal Problem, we can define the Lagrangian function, which is considered as the weighted sum of the objective function and constraints:

$$\begin{aligned}
L(T_i, \varepsilon) = {} & \left[\left(1 - \frac{m_i(T_i)}{L-1}\right)\lambda R_i e^{-\lambda n_i(T_i) R_i}\right] \\
& + \varepsilon_1[n_i(T_i) - m_i(T_i) - 1] \\
& + \varepsilon_2[n_i(T_i) - L] \\
& + \varepsilon_3[m_i(T_i) - L + 1] \\
& + \varepsilon_4[T_i - TTL_i]
\end{aligned} \tag{2}$$

where ε_x is *Lagrange Multiplier*. Note that TTL_i and L are constant values, and $R_i = TTL_i - T_i$. Then, we can easily obtain the Lagrangian dual function as follows.

$$\begin{aligned}
D(\varepsilon) &= \inf_{T_i}[L(T_i, \varepsilon)] \\
&= \inf_{T_i}\left\{\left[\left(1 - \frac{m_i(T_i)}{L-1}\right)\lambda R_i e^{-\lambda n_i(T_i) R_i}\right]\right. \\
&+ \varepsilon_1[n_i(T_i) - m_i(T_i) - 1] \\
&+ \varepsilon_2[n_i(T_i) - L] \\
&+ \varepsilon_3[m_i(T_i) - L + 1] \\
&+ \left.\varepsilon_4[T_i - TTL_i]\right\}.
\end{aligned} \tag{3}$$

Next, the first derivation of $L(T_i, \varepsilon)$ can be calculated as:

$$\begin{aligned}
\nabla L(T_i, \varepsilon) = {} & \left[-\frac{\nabla m_i(T_i)}{L-1}\lambda R_i e^{-\lambda n_i(T_i) R_i} + \left(1 - \frac{m_i(T_i)}{L-1}\right)\cdot\right. \\
& \left(\lambda \nabla R_i e^{-\lambda n_i(T_i) R_i} - \lambda^2 {R_i}^2 e^{-\lambda n_i(T_i) R_i} \nabla n_i(T_i)\right. \\
& \left.\left. - \lambda^2 R_i e^{-\lambda n_i(T_i) R_i} n_i(T_i) \nabla R_i\right)\right] \\
& + \varepsilon_1\left[\nabla n_i(T_i) - \nabla m_i(T_i)\right] \\
& + \varepsilon_2 \nabla n_i(T_i) + \varepsilon_3 \nabla m_i(T_i) + \varepsilon_4.
\end{aligned} \tag{4}$$

Let $\nabla L(T_i, \varepsilon) = 0$; we can achieve the relationship between T_i and ε. We assume that $T_i = g(\varepsilon)$, and then substitute T_i by using $g(\varepsilon)$ in (3). Thus, we can obtain the objective function $D(\varepsilon)$ in the dual problem as:

$$\begin{aligned}
D(\varepsilon) = {} & \left[\left(1 - \frac{m_i\left(g(\varepsilon)\right)}{L-1}\right)\right. \\
& \left.\cdot \lambda\left(TTL_i - g(\varepsilon)\right) e^{-\lambda n_i(g(\varepsilon))(TTL_i - g(\varepsilon))}\right] \\
& + \varepsilon_1\left[n_i\left(g(\varepsilon)\right) - m_i\left(g(\varepsilon)\right) - 1\right] \\
& + \varepsilon_2\left[n_i\left(g(\varepsilon)\right) - L\right] \\
& + \varepsilon_3\left[m_i\left(g(\varepsilon)\right) - L + 1\right] \\
& + \varepsilon_4\left[g(\varepsilon) - TTL_i\right].
\end{aligned} \tag{5}$$

Finally, we can get the dual problem as follows.

Dual Problem:

$$\begin{array}{rl} \textbf{max} & D(\varepsilon) \\ \textbf{Subject to:} & \varepsilon_1 \geq 0 \\ & \varepsilon_2 \geq 0 \\ & \varepsilon_3 \geq 0 \\ & \varepsilon_4 \geq 0 \end{array}$$

The first derivative of $D(\varepsilon)$ can be calculated as:

$$\begin{aligned} &\nabla D(\varepsilon) \\ &= \Bigg[-\frac{\nabla m_i\left(g(\varepsilon)\right)\nabla g(\varepsilon)}{L-1} \cdot \lambda\left(TTL_i - g(\varepsilon)\right) e^{-\lambda n_i(g(\varepsilon))(TTL_i - g(\varepsilon))} \\ &\quad + \left(1 - \frac{m_i\left(g(\varepsilon)\right)}{L-1}\right) \\ &\quad \cdot \Big(-\lambda \nabla g(\varepsilon) e^{-\lambda n_i(g(\varepsilon))(TTL_i - g(\varepsilon))} \\ &\quad - \lambda^2 \left(TTL_i - g(\varepsilon)\right)^2 e^{-\lambda n_i(g(\varepsilon))(TTL_i - g(\varepsilon))} \nabla n_i\left(g(\varepsilon)\right) \nabla g(\varepsilon) \\ &\quad + \lambda^2 \left(TTL_i - g(\varepsilon)\right) e^{-\lambda n_i(g(\varepsilon))(TTL_i - g(\varepsilon))} n_i\left(g(\varepsilon)\right) \nabla g(\varepsilon) \Big) \Bigg] \\ &+ \varepsilon_1 \left[\nabla n_i\left(g(\varepsilon)\right) \nabla g(\varepsilon) - \nabla m_i\left(g(\varepsilon)\right) \nabla g(\varepsilon)\right] \\ &+ \varepsilon_2 \nabla n_i\left(g(\varepsilon)\right) + \varepsilon_3 \nabla m_i\left(g(\varepsilon)\right) \nabla g(\varepsilon) + \varepsilon_4 \nabla g(\varepsilon). \end{aligned} \tag{6}$$

Let $\nabla D(\varepsilon) = 0$, we can determine the optimal solution of the dual problem, which is noted as ε^*. Because $T_i = g(\varepsilon)$, the optimal solution of the primal problem is: $T_i{}^* = g(\varepsilon^*)$. Hence, we can make a decision on which message should be dropped in order to maximize the average delivery rate. According to (1), we know that the dropped message is message i:

$$i = \left(1 - \frac{m_i(T_i{}^*)}{L-1}\right) \lambda(TTL_i - T_i{}^*) e^{-\lambda n_i(T_i{}^*)(TTL_i - T_i{}^*)}. \tag{7}$$

IV. PERFORMANCE EVALUATION

A. Simulation Environment

We implemented the epidemic routing via the proposed optimal buffer scheme using the ns-2 simulator. The version of ns-2 used in our simulation is ns-2.33. The implementation of our proposed improved epidemic routing with the optimal buffer scheme is based on the Monarch [28] extensions to ns-2. Monarch extends ns with radio propagation that models signal capture and collision. The simulator also models node mobility, allowing for experimentation with ad hoc routing protocols that must cope with the frequently changing network topology. Finally, Monarch implements the IEEE 802.11 [31] medium access control (MAC) protocol.

Unless otherwise noted, our simulations are run with the following parameters. We model 20, 50, 80 and 100 mobile nodes moving in a square area of 1000 m × 1000 m. Each node moves in the square with a speed uniformly distributed between $0 - 5$ meters/sec. The radio transmission range is assumed to be from 10 to 100 meters, and a two-ray ground reflection propagation channel is considered. The buffer size varies from 10 to 1000. The parameters for the simulation are given in Table 2 in detail. Most other parameters use the ns-2 defaults. Nodes move according to the well-known Random Waypoint mobility model.

Table 2. Parameters used in the simulation.

Parameter	Value
Number of node	20, 50, 80, 100
Mobility model	Random Waypoint
MAC	IEEE 802.11 DCF
Traffic source	CBR for UDP-based traffic
Node speed	$0 - 5$ meter/sec
Propagation model	Two-ray ground reflection
Simulation time	500 seconds
Data transmission rate	2 Mbps
Radio transmission range	10, 20, 50, 100 meters
Buffer size	10, 50, 100, 500, 1000

B. Network Model

In order to simplify the simulation without loss of generality, nodes are first regularly deployed in the area and then randomly move in accordance with the Random Waypoint mobility model. In our network simulation, the TTL value of each message is set to be 10 sec. We would like to emphasize that we use the discrete time sequence[1] in our simulation. Time value is only chosen from the integer value. In addition, the message transmission is from one node to its neighbors within its transmission range. We assume that the time period of each transmission and reception process is 1 sec. One example of 100 initial nodes deployment is shown in Fig. 2, where the source node is located at the corner of the square. In Fig. 2, we assume that node a is the source node. At 1 sec, node a generates a message i. Then, node a transmits this message to its neighbors within its transmission range. As we know, the time period of each transmission and reception process is 1 sec and the TTL value of each message is 10 sec. According to the deployment in Fig. 2, we can infer that the message transmission from the source node can cover at least 55%[2] nodes before the TTL value of the message is invalid. In this case, the buffer scheme should be fully engaged to handle the drop sequence of messages when the nodes buffers are full, since only the source of the message keeps a copy of it during the whole TTL duration, while intermediate nodes are not obliged to do so.

According to the deployment in Fig. 2, for message i, we can infer that

$$m_i(T_i) = \begin{cases} \sum_{T_i=1}^{TTL_i} T_i - 1\,, & 1 \leq T_i \leq TTL_i \\ 0\,, & T_i \geq TTL_i \end{cases} \tag{8}$$

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[1] Continuous time sequence can also be similarly performed in the simulation. We need only to change $\sum$ to $\int$ to obtain the equations in continuous time sequence.

[2] If the nodes are static, then the message transmission from the source node can cover 55% nodes. In the simulation, the nodes randomly move with a speed uniformly distributed between $0 - 5$ meters/sec., so the coverage percentage of message transmission from the source node must be larger than 55% due to the mobility.

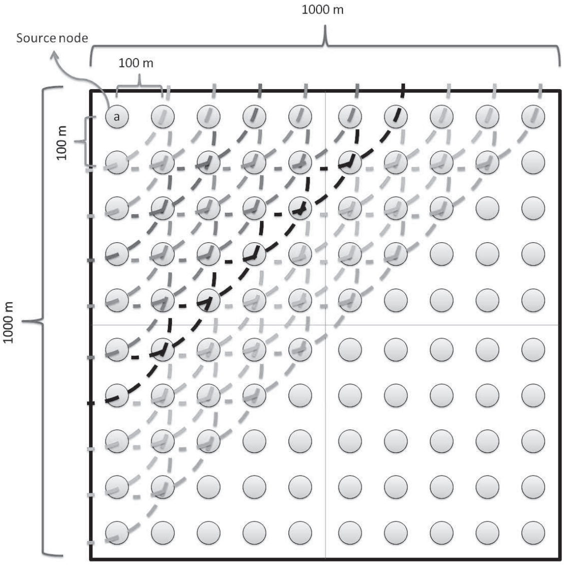

Fig. 2. 100 initial nodes deployment when the source node is located at the corner of the square.

In addition, we assume that each node can drop message i with probability ρ, which is determined by the buffer size. If the buffer size is set to be 10, then $\rho = 0.1$. Note that buffer size of 10 implies that the maximum number of messages stored in the buffer is 10. Each message (excluding the source message) has the same probability to be dropped by the node when the buffer is full. Hence, the node can drop message i with probability $\rho = 1/10 = 0.1$ when the buffer size is 10. Similarly, when the buffer size is chosen as 50, 100, 500, and 1000, the node can drop message i with probability $\rho = 1/50 = 0.02$, $\rho = 1/100 = 0.01$, $\rho = 1/500 = 0.002$ and $\rho = 1/1000 = 0.001$, respectively. From (4), we can obtain that

$$n_i(T_i) = \begin{cases} \sum_{T_i=1}^{TTL_i} T_i - \left(\sum_{T_i=1}^{TTL_i} T_i - 1\right) \cdot \rho\,, & 1 \le T_i \le TTL_i \\ 0\,, & T_i \ge TTL_i. \end{cases} \tag{9}$$

It is worth noting that ${T_i}^*$ is the optimal solution of the primal problem, which has been defined in Section III-A. When we get ${T_i}^*$, we can further make a decision to drop message i according to (7). First, we can determine the optimal solution ε^* of the dual problem by setting $\nabla D(\varepsilon) = 0$ according to (6). Then, we can obtain the optimal solution ${T_i}^*$ of the primal problem by calculating ${T_i}^* = g(\varepsilon^*)$. Here, in order to simplify the calculation, we assume that $\varepsilon_1 = \varepsilon_2 = \varepsilon_3 = \varepsilon_4 = \varepsilon$. In our paper, when we decide the value of ρ based on different buffer size, we can obtain $m_i(T_i)$ and $n_i(T_i)$ according to (8) and (9). Then, we can determine the optimal solutions ${T_i}^*$ under different values of ρ by substituting $m_i(T_i)$ and $n_i(T_i)$ in (4) and (6). For example, when $\rho = 0.1$, the calculated optimal solution ${T_i}^*$ of the primal problem is ${T_i}^* = 2$. Other optimal solutions of the primal problem under different values of ρ can be similarly achieved, which are listed in Table 3.

Table 3. Optimal solutions under different values of ρ when the source node is located in the corner of the square.

ρ	0.1	0.02	0.01	0.002	0.001
${T_i}^*$	2	4	5	5	6

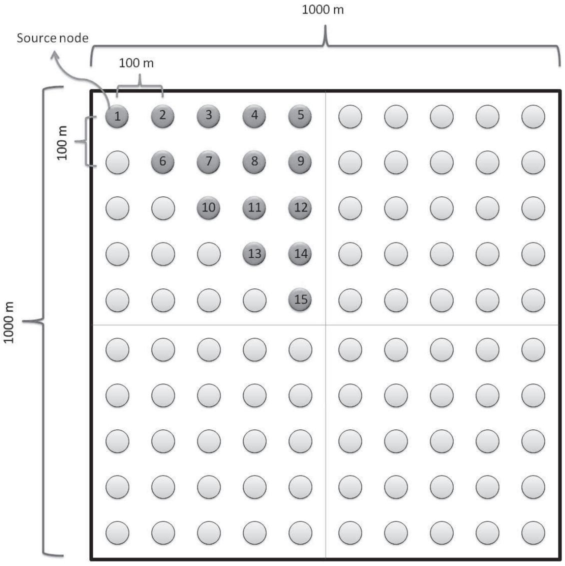

Fig. 3. Different source node locations in 100 initial nodes deployment (highlighted by orange color).

In 100 initial nodes deployment, the location of source node is very important. A different source node location will give rise to a different coverage percentage of message transmission as well as different buffer size utilization. Due to the symmetrical characteristic of the square, there are 15 different locations of the source node in all, which are highlighted in Fig. 3. Accordingly, the different coverage percentages of message transmission from the source node and the different optimal solutions are listed in Table 4. Note that the calculations of $m_i(T_i)$ and $n_i(T_i)$ are distinct in different source node locations[3].

C. Results and Discussion

Our simulation includes four parts. First of all, we only focus on reporting the comparative simulation results about packet delivery rate and average end-to-end delay of the proposed scheme itself with respect to different buffer size and distinct source node location. The buffer size is changed from 10 to 1000 and the source node location varies from $Location = 1$ to $Location = 7$. Note that the number of nodes is set to be 100, the radio transmission range is set to be 100 m, and other simulation parameters use the defaults. While the buffer size is changed during a simulation, the source node location is fixed as $Location = 1$. Conversely, the buffer size is fixed as 50 when the source node location is changed.

In the second part, we present a comparative simulation analysis among the proposed scheme, original epidemic routing [4], TSMF [27], and LDPR [11] in terms of packet delivery rate and average end-to-end delay with respect to different buffer

[3] In a real deployed system, each node can be aware of the global information by resorting to the anchor node, which is similar to that in [11]. In fact, [11] has already demonstrated that the deployment of some anchor nodes in a certain area can help to gather and distribute the global information without affecting the performance of the routing protocol.

Table 4. Different coverage percentages of message transmission from the source node and different optimal solutions.

Location	Coverage percentage	Optimal solutions				
		$\rho = 0.1$	$\rho = 0.02$	$\rho = 0.01$	$\rho = 0.002$	$\rho = 0.001$
1	55%	2	3	5	5	6
2	63%	2	4	4	5	6
3	69%	3	4	5	5	7
4	73%	3	5	6	6	7
5	75%	4	5	6	7	8
6	72%	4	6	6	7	8
7	78%	4	6	7	7	8
8	82%	5	6	7	8	9
9	84%	5	7	7	8	9
10	85%	5	7	8	8	9
11	89%	6	6	8	8	9
12	91%	7	7	8	8	9
13	94%	7	7	8	9	9
14	96%	7	8	9	9	9
15	99%	8	8	9	9	9

size. TSMF is chosen as a comparison object since TSMF targets to increase to the delivery rate even though it uses the message size to optimize the buffer scheme, while LDPR is chosen as a comparison object since an intelligent buffer management scheme is proposed in it. The range of variation of buffer size is from 10 to 1000. Note here that the number of nodes and the radio transmission range are set as the same as that in part one.

In the third part, we concentrate on comparing the proposed scheme with other protocols with respect to different node density. The number of nodes varies from 20 to 100. In this scenario, the buffer size is fixed as 50 and the radio transmission range is set to be 100 m. Similarly, in the fourth part, we focus on comparing the proposed scheme with other protocols with respect to different radio transmission range. The radio transmission range is changed from 10 m to 100 m. In this case, the number of nodes is fixed as 100 and the buffer size is set to be 50.

C.1 Performance Comparison of the Proposed Scheme Itself

We know that the coverage percentage is the lowest when the source node is located at the corner of the square. In this case, the buffer scheme should be fully engaged to handle the drop sequence of messages when the nodes buffers are full, since only the source of the message keeps a copy of it during the whole TTL duration while intermediate nodes are not obliged to do so. Location 1 is an extreme scenario. We compare the packet delivery rate under different buffer sizes when the source node is in Location 1, which is summarized in Table 5. From Table 5, we can find that the packet delivery rate increases as the buffer size increases. In addition, we can conclude that the packet delivery rate is the lowest when $\rho = 0.1$. In Table 6, we also summarize the comparison results of the average end-to-end delay under different buffer sizes when the source node is in Location 1. Similar to Table 5, we can conclude that the average end-to-end delay is the longest when $\rho = 0.1$. Table 5 and Table 6 indicate that the performance of the proposed scheme is the worst when we choose $\rho = 0.1$. Hence, in the following simulation, we choose $\rho = 0.1$ as the baseline. If the performance of the proposed optimal buffer scheme outperforms that of the original epidemic routing, TSMF and LDPR when $\rho = 0.1$, then we believe that the performance of the proposed optimal buffer scheme is the best among all cases.

Next, we compare the performance of the proposed optimal buffer scheme under different source node locations. The comparison results are presented in Table 7 and Table 8, where the buffer size is fixed as 50. From Table 7 and Table 8, we can conclude that the performance of the proposed scheme is the worst when the source node is located at Location 1. It indicates that the performance of the proposed scheme will be better than that of the original epidemic routing, TSMF and LDPR, if it outperforms its competitors when $Location = 1$. Therefore, we choose $Location = 1$ as the baseline[4] in the following simulation.

C.2 Effect of Buffer Size

We now compare the performance of packet delivery rate and average end-to-end delay among the proposed scheme and other protocols with respect to different buffer size.

We choose buffer size as the parameters of X axis and consider the packet delivery rate and average end-to-end delay as the parameter of Y axis, respectively. For observing the impact on the performance of protocols caused by the change of buffer size, we set the number of nodes at 100 and the radio transmission range at 100 m without thinking about other circumstances. Figs. 4 and 5 show the details of the comparison results. The first interesting aspect that we analyze is the packet delivery rate, a characteristic aspect of a protocol for delay tol-

[4] In Table 7 and Table 8, we summarize the packet delivery rate and the average end-to-end delay on the basis of different source node locations. When $Location \geq 8$, the values of packet delivery rate are all equal to 100% and those of the average end-to-end delay are 60. Thus, we omit the items from $Location = 8$ to $Location = 15$.

Table 5. Packet delivery rate versus buffer size under location 1.

Buffer size	Packet delivery rate				
	$\rho = 0.1$	$\rho = 0.02$	$\rho = 0.01$	$\rho = 0.002$	$\rho = 0.001$
10	47.2%	48.8%	49.3%	50.1%	50.9%
50	95.8%	96.1%	96.9%	97.2%	97.5%
100	98.1%	98.5%	99.1%	99.4%	99.7%
500	100%	100%	100%	100%	100%
1000	100%	100%	100%	100%	100%

Table 6. Average end-to-end delay versus buffer size under location 1.

Buffer size	Average end-to-end delay				
	$\rho = 0.1$	$\rho = 0.02$	$\rho = 0.01$	$\rho = 0.002$	$\rho = 0.001$
10	91.39	82.41	78.83	70.45	62.38
50	108.33	100.21	89.93	81.71	74.26
100	122.27	112.33	100.33	92.36	81.53
500	116.69	102.39	91.19	85.59	72.39
1000	121.76	109.87	91.19	83.87	76.87

Table 7. Packet delivery rate under different locations when buffer size is 50.

Location	Packet delivery rate				
	$\rho = 0.1$	$\rho = 0.02$	$\rho = 0.01$	$\rho = 0.002$	$\rho = 0.001$
1	95.8%	96.1%	96.9%	97.2%	97.5%
2	96.1%	96.6%	97.4%	98.1%	98.9%
3	96.7%	97.2%	97.9%	98.7%	99.5%
4	97.3%	97.8%	98.4%	99.2%	100%
5	98.4%	98.8%	99.1%	99.6%	100%
6	99.5%	99.7%	100%	100%	100%
7	99.7%	99.9%	100%	100%	100%

Table 8. Average end-to-end delay under different locations when buffer size is 50.

Location	Average end-to-end delay				
	$\rho = 0.1$	$\rho = 0.02$	$\rho = 0.01$	$\rho = 0.002$	$\rho = 0.001$
1	108.33	100.21	89.93	81.71	74.26
2	98.39	89.73	80.21	70.66	63.65
3	90.67	81.27	73.92	64.98	60.95
4	82.33	75.82	69.43	62.27	60.27
5	74.47	69.81	63.18	61.66	60.32
6	65.55	63.71	61.67	60.47	60.35
7	60.33	60.57	60.22	60.38	60.28

erant networks. As shown in Fig. 4, the packet delivery rate increases as the buffer size increases. All the curves sharply rise up until the buffer size is 100 and then gradually go up until they reach 100% packet delivery rate. This is intuitive, since a larger buffer size means that there is enough space in a node to store larger numbers of packets so as to guarantee the packets' lifetime and delivery. Note that, in order to simplify the presentation, we use Optimal to denote the improved epidemic routing with the proposed optimal buffer scheme. In particular, the packet delivery rate of Optimal performs well with a very small buffer size. When the buffer size is only 50, the packet delivery rate of Optimal can still be 95.8% which can satisfy general communication demand. Comparing them, it is easy to say that Optimal is the best with respect to the packet delivery rate. This is due to the fact that Optimal effectively utilizes and manages the buffer size by using the proposed optimal buffer scheme. Another aspect we analyzed is the average end-to-end delay. It is of interest to find out how much time it takes for a message to be delivered. The average end-to-end delay can reflect the difference of delivery time in order to make a better choice in the complicated environment of real DTN applications. Observed from Fig. 5, the average end-to-end delay of all protocols hastily increases until the buffer size is 100, and then declines a little as the buffer size further increases. When the buffer size is over 100, there is enough space to store and manage packets so that the change in the delay is not intense. From Fig. 5, we can also find that, on the one hand, the average end-to-end delay of Optimal is a little longer than that of LDPR when the buffer size is less than 100. This is because Optimal should frequently calculate the optimal solution to find the dropping message i. On the other hand, the average end-to-end delay of Optimal is the lowest when the buffer size is larger than 100. This is because Optimal can efficiently manage the node buffer and optimize the message dropping sequence by the proposed optimal buffer scheme.

C.3 Effect of Node Density

In this subsection, we analyze the influence of node density. Note that the number of nodes can be chosen as 20, 50, 80, and 100. X axis represents the number of nodes and Y axis indicates the packet delivery rate or average end-to-end delay. In these scenarios, we fix the buffer size as 50 and the radio transmission range as 100 m so as to observe the impact of different node density on the performance. Figs. 6 and 7 show the details of the comparison results.

Viewed from Fig. 6, we note that the packet delivery rate increases as the number of nodes rises. This is intuitive, since a higher node density means that nodes have more probability to meet with each other. The packet delivery rate of Optimal is the largest compared with the others. It is worth noting that only Optimal can maintain a high delivery rate when the number of nodes reaches 50. Fig. 7 represents the phenomenon that the average end-to-end delay decreases as the number of nodes rises. Note that Optimal has the lowest average end-to-end delay in all cases of the number of nodes compared with the others. It is noteworthy that the average end-to-end delay of all the protocols hastily decreases until the number of nodes is 50, and then declines gradually as the number of nodes further increases. When the number of nodes is very small, the successful packet deliveries are limited. Any packet wanting to be transmitted to some farther destination could be dropped due to the low node density. Yet, more and more packets can be successfully delivered to their destinations with an increase in the number of nodes. Simultaneously, the average end-to-end delay decreases.

C.4 Effect of Radio Transmission Range

Another aspect we observed is that the influence of radio transmission range. Here, X axis represents the radio transmission range, while Y axis still indicates the packet delivery ratio or average end-to-end delay. Note that we fix the number of nodes as 100 and the buffer size as 50. Figs. 8 and 9 illustrate the influence of radio transmission range on the performance of protocols.

Observed from Fig. 8, in the extreme conditions where the radio transmission range is only 10 m, Optimal still outperforms the other three protocols. It indicates that Optimal has enough ability to adapt to a complex environment of real applications. When the radio transmission range increases to 20 m, the packet delivery rate of Optimal is 93.9% which can still ensure successful packet delivery. Fig. 9 depicts the comparison result of average end-to-end delay among the routing protocols. In particular, the average end-to-end delay of Optimal reaches 108 sec when the radio transmission range is 100 m, while that of EPI, TSMF and LDPR come up to 228 sec, 355 sec and 138 sec. In the worst case, when the radio transmission range is only 10 m, then the average end-to-end delay of the entire protocols trend to be infinite. Optimal has the lowest average end-to-end delay among the protocols determined from the curves.

In summary, Optimal can effectively drop those useless messages and maintain those useful messages as long as possible based on the global information so as to optimize the message dropping sequence and manage the buffer size efficiently. As a consequence, Optimal can increase the packet delivery rate and decrease the average end-to-end delay even in the extreme conditions.

V. CONCLUSIONS

In this paper, we have proposed an optimal buffer scheme in epidemic routing, which is based on the Lagrangian and dual problem models. By using the proposed optimal buffer scheme, the packet delivery rate in epidemic routing is considerably improved, even under the condition of a fixed buffer size in a node. Our simulation results show that epidemic routing with the proposed optimal buffer scheme outperforms the original epidemic routing, TSMF and LDPR in terms of packet delivery rate and average end-to-end delay. It is worth noting that the improved epidemic routing requires much less buffer size compared to the original epidemic routing in order to ensure the same packet delivery rate. Consequently, the proposed optimal buffer scheme makes the improved epidemic routing very practical and valuable. In addition, the proposed optimal buffer scheme can make the epidemic routing in DTNs satisfy the general communication demand. It can be easily inferred that the proposed optimal buffer scheme in epidemic routing is very attractive to real DTN applications.

In our simulation, in order to simplify the calculation, we compute the optimal solution under the discrete time sequence. In the future, we will evaluate the performance of the optimal buffer scheme by changing the discrete time sequence to continuous time sequence.

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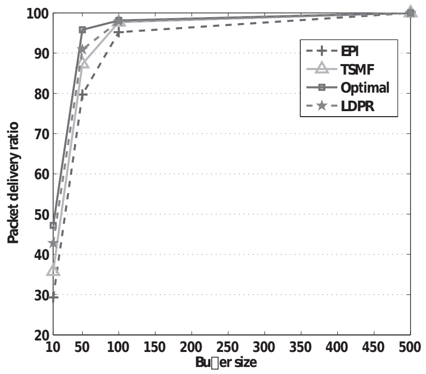

Fig. 4. Packet delivery rate versus buffer size.

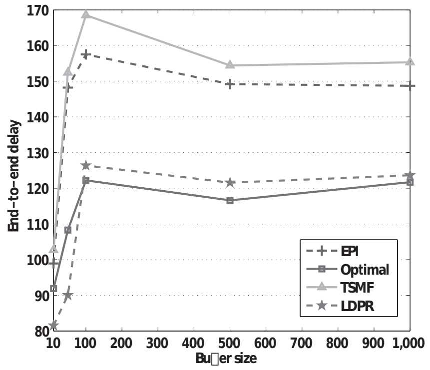

Fig. 5. Average end-to-end delay versus buffer size.

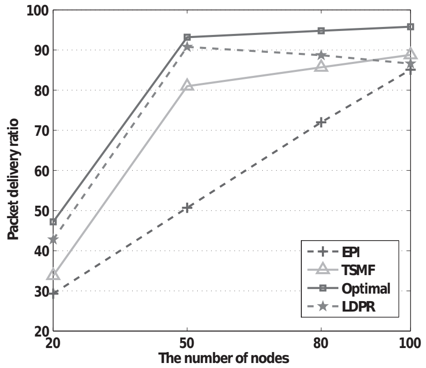

Fig. 6. Packet delivery rate versus the number of nodes.

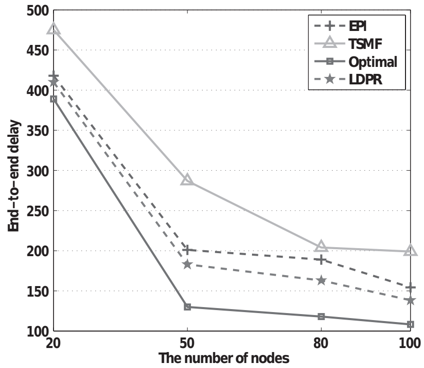

Fig. 7. Average end-to-end delay versus the number of nodes.

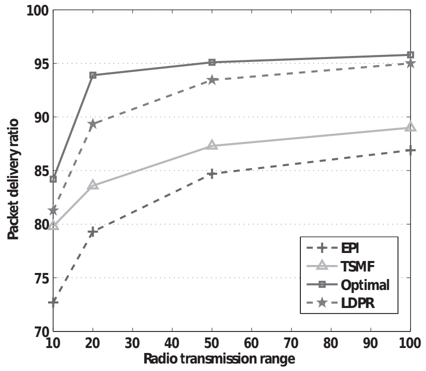

Fig. 8. Packet delivery rate versus radio transmission range.

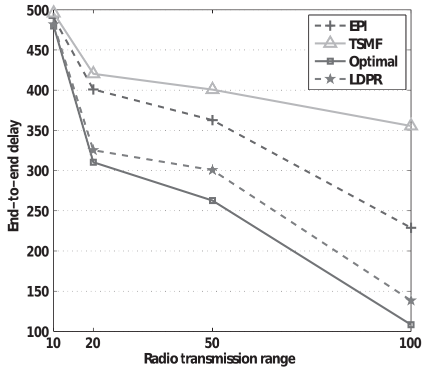

Fig. 9. Average end-to-end delay versus radio transmission range.

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