Contact Duration Aware Data Replication in DTNs with Licensed and Unlicensed Spectrum

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Abstract—The recent popularization of hand-held mobile devices, such as smartphones, enables the inter-connectivity among mobile users without the support of Internet infrastructure. When mobile users move and contact each other opportunistically, they form a delay tolerant network (DTN), which can be exploited to share data among them. Data replication is one of the common techniques for such data sharing. However, the unstable network topology and limited contact duration in DTNs make it difficult to directly apply traditional data replication schemes. In this paper, we recognize the deficiency of existing data replication schemes which treat the complete data item as the replication unit, and propose to replicate data at the packet level using erasure coding techniques. Our study consists of two cases based on the operating spectrum: unlicensed spectrum and licensed spectrum. For both cases, we analytically formulate the data replication problem as a mixed integer programming problem and propose a practical algorithm which operates in a fully distributed manner. Extensive simulations on both synthetic and realistic traces show that our scheme outperforms other existing replication schemes in terms of successful data retrieval probability in various scenarios.

Index Terms—Data replication, delay tolerant networks, contact duration, cognitive radio, erasure coding

1 Introduction

Due to the recent popularization of hand-held mobile devices, such as smartphones, there arises the requirement to effectively distribute data to those devices. Such data can generally be distributed from the service provider to mobile users via cellular networks. However, it has been recently reported that the excessive traffic demands are overloading the cellular network infrastructure [1]. To address this problem, some recent studies [2], [3] have proposed to utilize the mobility and the subsequent opportunistic contacts of the users to offload part of the cellular traffic, especially for the bandwidth-eager traffic, such as video clips. Particularly, the mobile devices with short-range wireless interfaces can form a Delay Tolerant Network (DTN) [4] by exploiting their peer-to-peer opportunistic connectivity. A mobile user downloads and replicates data from the service provider when it has a low-cost connection to the access points (APs), such as WiFi hotspots, and then distributes data to other peer users when they contact each other via DTNs.

Data replication has been widely used to improve the performance of data access in traditional wired/wireless networks [5], [6], [7]. With data replication, users can access the data without the support of network infrastructure, and can reduce the traffic load of the infrastructure. In delay tolerant networks, mobile users contact each other opportunistically, so it may take a long time for the data requester to contact the data source and access the data. By replicating data at multiple nodes, the data can be accessed at multiple places, and hence reducing the data access delay. Here the fundamental question is: how to determine the optimal replication strategy to better utilize the limited storage space and the transmission bandwidth. However, existing data replication techniques cannot be directly applied to DTNs which are characterized by unstable network topology and limited contact duration.

The challenge of unstable network topology has been well studied in data forwarding in DTNs, and addressed by exploiting node mobility model [8] or using social network theory [9], [10]. Existing works on data replication in DTNs [11], [12] address this challenge by modeling the contact processes as a Poisson distribution according to the contact histories. However, these works ignore the contact durations limits. They simply assume that the complete data can always be transmitted as long as a requester contacts a node storing the data. In other words, they consider a data item as integral during data replication. A node either replicates the complete data, or does not replicate it at all. This methodology is referred to as *data-level replication*.

Unfortunately, in reality, the contact duration is usually short due to node movement and the limited range of peer-to-peer wireless communication. For example, when hand-held devices communicate via Bluetooth, which supports a data rate of up to 2.1 Mbps and a typical wireless range of about 10 meters, the contact duration tends to be as short as several seconds if the users are moving at a walking speed. When the users are in the high speed vehicles, even if they

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communicate via WiFi (802.11g) which has a faster data rate (up to 54 Mbps) and a longer range (up to 38 m indoors/ 140 m outdoors), the contact duration is still short. Moreover, the achievable data rate is far less due to the interference from many other devices which also operate on this spectrum. The transmission of large multimedia content, such as video, further exacerbates the impact of the limited contact duration on data replication.

One way to address the aforementioned problem is to opportunistically use the under-utilized licensed spectrum (e.g., TV channels) to increase the data transmission capacity with cognitive radio techniques. For example, if we use 802.11af to access the licensed spectrum between 54 and 790 MHz, the maximum data rate per channel is 26.7 Mbps with range of up to 1 km. In practice, by aggregating continuous channels together, the actual data rate can be much higher than 26.7 Mbps and even outperform the unlicensed spectrum. This licensed spectrum also provides much longer transmission range which further increases the data transmission capacity upon contact. However, the design of appropriate data replication strategies on these channels will become more complex, since we not only need to consider the node contact pattern and the contact duration, but also the primary (licensed) user appearance which affects the number of channels available for data transmission.

In this paper, we identify the deficiency of traditional data-level replication in realistic DTN environments. To better utilize the network resource, we adopt the erasure coding technique [13] to encode a data item into multiple coded packets, and propose *packet-level replication* for DTNs. Our study consists of two cases based on the operating channels: unlicensed channels and licensed channels. The unlicensed channels are always available to mobile users but usually congested, whereas the licensed channels are highly underutilized but may be unavailable from time to time when primary users appear. For both cases, we focus on appropriately determining which data items and how many packets to replicate at each node. The decision will be based on node mobility pattern, data access pattern and even appearance pattern of primary users. Extensive synthetic and trace-driven simulations validate that our solution outperforms other existing replication schemes in terms of successful data retrieval probability in various scenarios.

The rest of the paper is organized as follows. Section 2 reviews the related work. Section 3 presents an overview of the network model and the basic idea of our design. We provide a formal problem definition in Section 4 and then describe how to perform data replication for both unlicensed spectrum case and licensed spectrum case in Sections 5 and 6 respectively. The results on both synthetic and trace-driven performance evaluation are presented in Section 7, and Section 8 concludes the paper.

2 Related Work

To increase the performance of data access in DTNs, many existing works focus on the topic of data dissemination. In [14], a broadcasting based data dissemination approach is implemented. In [15], the authors provide theoretical analysis to the stationary and transient regimes of data dissemination. Some later solutions disseminate data based on a pub/sub structure, in which the data is classified into some pre-defined channels, and disseminated based on user's subscriptions [16].

Recently, caching solutions have been proposed to improve the performance of data access in DTNs. For example, Gao et al. [17] propose to intentionally cache data at a set of network central locations which can be easily accessed by other nodes, but the contact duration limitation has not been taken into account. Zhuo et al. [18] considers the effects of contact duration on caching, but the analysis is limited to a given fixed number of replicas for a data item.

Data replication is another solution to improve data access, which has been well studied in unstructured peer-to-peer systems [7], [19]. In [7], Cohen and Shenker prove that the square-root allocation strategy can minimize the expected search size on successful queries. In [19], Tewari and Kleinrock show that if the nodes use an expanding ring search, the proportional allocation strategy can lead to optimal performance. Data replication problem becomes even tough under heterogenous network environments. The problem of determining the optimal replication solution in a heterogeneous network is similar to the facility location problem and the K-median problem, and both of them are proved to be NP-hard. A 20.5-approximation algorithm for the data replication problem with uniform-size data items in heterogeneous networks has been proposed in [6]. Later, Tang and Rajaraman [5] design a polynomial-time centralized replication algorithm which can achieve a four-approximation solution, and a localized distributed algorithm in heterogeneous ad hoc networks. However, these data replication schemes cannot be applied to DTNs.

In [11], a distributed data replication scheme has been proposed for DTNs which considers the impatience of the nodes towards the query delay of different data types. This scheme is based on the assumption of homogeneity, i.e., all nodes in the network have the same preferences and mobility pattern. Later, Loannidis et al. [12] formulate the data replication problem in heterogeneous DTNs, and design a fully distributed replication algorithm. However, these works do not consider the contact duration limits, and simply assume that as long as a data requester contacts a replicating node, the complete requested data can be retrieved. In contrast, our proposed approach considers limited data transmission capacity upon contact and replicates data at the packet-level.

This paper substantially extends the preliminary version [20] where we mainly focused on how to perform data replication in the unlicensed spectrum case. In this paper, we also leverage cognitive radios to improve data replication performance [21]. Most existing solutions in cognitive radios assume the existence of an end-to-end path between the data source and data requesters. They focus on designing efficient routing protocols to minimize the routing delay or maximize the throughput [22], [23]. In contrast, our proposed approach is designed for delay tolerant networks where users are only intermittently connected when they move into the communication range of each other.

3 Overview

In this section, we introduce the network model and the basic idea of our approach.

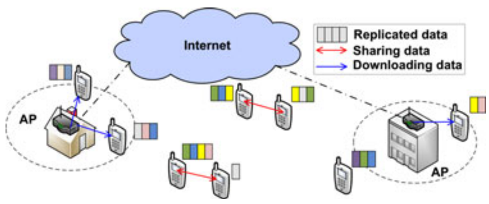


Fig. 1. Network scenario.

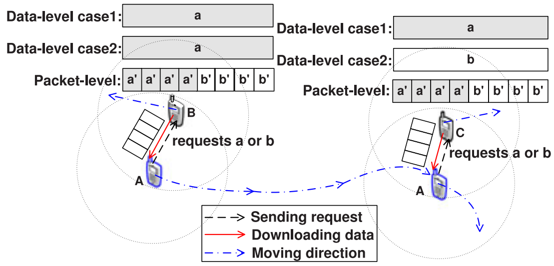


Fig. 2. An example of contact scenario.

3.1 Network Model

We consider a hybrid network scenario which includes APs and mobile nodes as shown in Fig. 1. The APs can connect to the data provider via the Internet. Mobile nodes download and replicate data when they move into the wireless range of the AP. We do not consider the contact duration limits between mobile nodes and APs, since the APs provide a relatively large coverage and the nodes are relatively static around APs, especially those at home or office. However, when mobile nodes are out of the AP's coverage, they can only share data with other peers. Thus, the mobiles nodes form a DTN to exchange their replicated data by opportunistic contacts. The amount of data that can be transmitted between two nodes is decided by their contact pattern such as contact frequency and contact duration, and the appearance pattern of primary users which affect the number of channels available for data transmission.

Due to mobility and limited range of the wireless communication, the contact duration is usually short. Thus, it is hard to transmit large amount of data such as video, especially considering that most mobile devices use unlicensed ISM channels for peer-to-peer communication. With cognitive radio techniques, the licensed channels can be opportunistically exploited to increase the data transmission capacity among these mobile devices. However, data access will be more complex, since we not only need to consider the probability of nodes reaching the destination, but also consider the data transmission capacity which is affected by the primary users who are licensed to access the channels. For example, if some contacts occur within the activity regions of the primary users, less amount of data can be transmitted during the data transmission time.

To address the aforementioned problem, we may simply fragment the data and only transmit a part of it during each contact. However, this simple fragmentation may result in the coupon collector's problem [24] which significantly decreases the efficiency of data access. To mitigate this problem, we adopt the erasure coding technique [13] to encode data into a large set of coded packets, and any sufficiently large subset of the packets can be used to reconstruct the data.

There are three typical coding schemes: Reed-Solomon (RS) codes, Tornado codes and LT codes. In general, any $s = (1+\epsilon)G/g$ coded packets of size g is needed to reconstruct the original data of size G. RS codes have $\epsilon = 0$, while Tornado codes and LT codes normally have $0 < \epsilon < 0.06$. Although Tornado codes and LT codes require slightly more packets to reconstruct the original data, they achieve a substantial improvement in encoding and decoding complexity. In particular, for LT codes, it can generate more distinct packets than the other two codes, and hence has the lowest probability for the data requester to receive useless duplicate packets among the three coding schemes. Thus, we use LT codes in our packet-level replication approach. Here the packet size g is a configurable parameter, which needs to balance the computation complexity and the transmission time. For example, increasing the packet size increases the successful transmission probability, which reduces the transmission time of the original data item. Meanwhile, the computation complexity may increase since the data has to be encoded into more packets.

3.2 Basic Idea

Our goal is to determine the replication solution for each node to fully utilize the network resources, such as the limited storage spaces that each node is willing to provide, and the limited node contact opportunities. Existing studies on data replication [5], [7], [11], [12] assume that the requester can always get the complete requested data from the replicating node, when a connection arises between them. They replicate data at data-level, i.e., a node either replicates the complete data or does not replicate any packet. However, in DTNs, when the contact duration is short or the operating channels are affected by primary users, the data transmission capacity upon contact is limited and a complete data item may not be fully transmitted to the requester. Next, we use a simple example to show the deficiency of employing the data-level replication.

As shown in Fig. 2, node A is a data requester, and it sequentially contacts node B and C when it moves. There are two equal-sized data items named a and b, and both of them can be cut into eight packets (not shown in the figure at data level). Both node B and C are only willing to provide limited buffers to replicate eight packets. During each contact, only half of the data (four packets) can be transmitted due to the contact duration limits. If data-level replication is conducted, B and C can only select either a or b to replicate. Since only half of the data can be transmitted during each contact, it cannot be used and has to be discarded. As can be seen, under the data-level replication, both the storage spaces and the contact opportunities have not been fully utilized.

To make better use of the resources by considering limited data transmission capacity upon contact, we propose to replicate data at the packet-level. As shown in Fig. 2, if node B and C replicate four distinct packets of both data item a and b respectively, node A can successfully download the complete data (four packets from B and four packets from C), no matter which data it requests. We can see that given the same network resource, packet-level replication outperforms data-level replication. Therefore, in this paper, we design data replication schemes at the packet-level.

4 Problem Definition

Suppose that there are N mobile nodes and M data items in the network, and each node, say i, is willing to provide a storage of size ρ_i for data replication. To simplify the presentation, we assume that all data items have the same size G, and each of them can be reconstructed by any $s = (1+\epsilon)G/g$ coded packets. We also assume that the data items have the same retrieval time constraint T. How to remove the two assumptions is discussed in [20]. Let matrix $\mathbf{x}$ represent the data replication solution, where each element $x_{i,d} \in \mathbf{x}$ denotes the number of packets of data d replicated at node i. Let variable $A_i^d(\mathbf{x})$ denote the total number of packets of data d that node i can retrieve from others within the time constraint, given a data replication solution $\mathbf{x}$. We aim to maximize the average successful data retrieval probability within the time constraint. We assume that the average inter-contact time between the mobile node and the AP is usually longer than the time constraint; otherwise, it is not attractive for the node to download data via DTN. Then, we have:

Definition 1. *The contact duration aware data replication problem is to determine the optimal data replication solution* $\mathbf{x}$ *to maximize the average data retrieval probability, subject to the storage constraint and the data retrieval time constraint.*

$$\max \sum_{d=1}^{M}\sum_{i=1}^{N} q_{i,d} P\big(A_i^d(\mathbf{x}) \geq s - x_{i,d}\big) \tag{1}$$

$$s.t.\ \forall x_{i,d} \in \mathbf{x},\ \ x_{i,d} \in \{0,\ldots,s\}, \tag{2}$$

$$\forall i \in \{1,\ldots,N\}, \sum_{d=1}^{M} x_{i,d} \leq \rho_i. \tag{3}$$

where $q_{i,d}$ is the query rate of node i to data item d, and $\sum_{i=1}^{N}\sum_{d=1}^{M} q_{i,d} = 1$. $q_{i,d}$ is decided by the data access pattern of the network. Constraint (2) ensures that every node replicates at most s packets for each data. Constraint (3) guarantees that the total number of packets replicated at each node is limited by the storage constraint of the node.

Though Definition 1 is straightforward, to get the optimal solution is quite complex. The main difficulty lies in deriving the closed form expression of the objective function. We know that $P(A_i^d(\mathbf{x}) \geq s - x_{i,d}) = \sum_{a=s-x_{i,d}}^{\infty} f_{A_i^d(\mathbf{x})}(a)$, where $f_{A_i^d(\mathbf{x})}(a)$ is the probability mass function (PMF) of $A_i^d(\mathbf{x})$. To obtain the closed form expression of the objective function, we try to calculate $f_{A_i^d(\mathbf{x})}(a)$.

For any node pair, say i and j, we set a random variable $Y_{i,j}$ to represent the maximum amount of data that can be sent during a contact between them. We further define a random variable $Z_{i,j}$ to denote the number of contacts happened between them within the time constraint. Then, $Y_{i,j}^{(1)}, Y_{i,j}^{(2)}, \ldots, Y_{i,j}^{(Z_{i,j})}$ are $Z_{i,j}$ i.i.d. variables which denote the maximum amount of data that can be sent during each contact between node i and j. The total amount of data that can be sent between them within the time constraint is denoted as $U_{i,j}$, and $U_{i,j} = Y_{i,j}^{(1)} + Y_{i,j}^{(2)} + \cdots + Y_{i,j}^{(Z_{i,j})}$.

Let $A_{i,j}^d(\mathbf{x})$ denote the number of the coded packets of data item d that node i can receive from node j within the time constraint given a replication solution $\mathbf{x}$. The PMF of $A_{i,j}^d(\mathbf{x})$ can be calculated as:

$$f_{A_{i,j}^d(\mathbf{x})}(a) = \begin{cases} \int_{ga}^{g(a+1)} f_{U_{i,j}}(u)\mathrm{d}u & 0 \leq a < x_{j,d} \\ \int_{ga}^{\infty} f_{U_{i,j}}(u)\mathrm{d}u & a = x_{j,d} \\ 0 & otherwise. \end{cases} \tag{4}$$

where $f_{U_{i,j}}(u)$ is the probability density function (PDF) of $U_{i,j}$. The PMF of $A_i^d(\mathbf{x}) = \sum_{j\neq i} A_{i,j}^d(\mathbf{x})$ can be derived as:

$$\begin{aligned} f_{A_i^d(\mathbf{x})}(a) &= f_{\sum_{j\neq i} A_{i,j}^d(\mathbf{x})}(a) = f_{A_{i,1}^d(\mathbf{x})}(a) \otimes \cdots \otimes \\ & f_{A_{i,i-1}^d(\mathbf{x})}(a) \otimes f_{A_{i,i+1}^d(\mathbf{x})}(a) \otimes \cdots \otimes f_{A_{i,n}^d(\mathbf{x})}(a), \end{aligned} \tag{5}$$

where $f_{A_i^d(\mathbf{x})}(a)$ is a discrete convolution of $f_{A_{i,j}^d(\mathbf{x})}(a)$, which can be derived from the PDF of $U_{i,j}$. However, since $U_{i,j}$ is the sum of a random number of random variables, its PDF has no closed form expression. As a result, we cannot derive the closed form expression of the objective function.

Next, to make the problem tractable, we isolate the variables in the objective function, and let the part which has no closed form only contain constants. Then, we give an approximate calculation on the part. We formulate the problem into a mixed integer programming (MIP) problem and solve it by using the CPLEX [25]. To make data replication more applicable to the practical use, we further design a polynomial time distributed algorithm based on the local knowledge of each node. Our study is divided into two cases based on the operating channels: unlicensed channels and licensed channels.

5 Contact Duration Aware Data Replication: The Unlicensed Spectrum Case

In this section, we first formulate the contact duration aware data replication problem under the unlicensed spectrum case and then propose a practical algorithm which operates in a fully distributed manner.

5.1 Problem Formulation and Analysis

5.1.1 MIP Formulation

Based on existing works [26], [27], we model the contact duration between nodes as a Pareto distribution. More specifically, for any node pair i and j, the maximum amount of data that can be sent during a contact between them (i.e., $Y_{i,j}$) follows Pareto distribution. Moreover, the number of contacts happened between them within the time constraint (i.e., $Z_{i,j}$) is assumed to follow Poisson distribution.

Let random variable $V_{i,j}$ denote the maximum number of packets that can be transmitted between node i and j within the time constraint. $V_{i,j}$ can be calculated as follows:

$$V_{i,j} = \begin{cases} \left\lfloor \frac{U_{i,j}}{g} \right\rfloor & \left\lfloor \frac{U_{i,j}}{g} \right\rfloor < s \\ s & \left\lfloor \frac{U_{i,j}}{g} \right\rfloor \geq s. \end{cases} \tag{6}$$

Each $V_{i,j}$ has $s+1$ possible integer values ranging from 0 to s. Specially, $V_{i,j} = s$ when the aggregated contact duration between the two nodes is long enough to transmit the complete data item. Therefore, the total number of packets that can be transmitted between node i and any other nodes form a $1 \times N$ vector $[V_{i,1}, V_{i,2}, \ldots, V_{i,N}]$. This vector falls into one of the $(s+1)^N$ possible combinations. We use a $1 \times N$ vector $\mathbf{v} = [v_1, v_2, \ldots, v_N]$ to denote one possible combination or say, a contact pattern in which v_j ($0 \leq v_j \leq s$, for $j = 1, \ldots, N$) packets can be transmitted from or to node j. There are totally $(s+1)^N$ possible patterns $\mathbf{v}$, and we define Φ as the set of total possible patterns. Let $P_i^{\mathbf{v}}$ denote the probability that node i follows the contact pattern $\mathbf{v} = [v_1, v_2, \ldots, v_N]$, i.e., $V_{i,j} = v_j$ for $j = 1, \ldots, N$. Due to the independent contact processes of node pairs, $P_i^{\mathbf{v}} = \prod_{j=1}^{N} P(V_{i,j} = v_j)$. Note that for all i, $P(V_{i,i} = s) = 1$ and $P(V_{i,i} \neq s) = 0$. The details on how to calculate $P_i^{\mathbf{v}}$ are provided in [20].

We further define a binary variable $R_d^{\mathbf{v}}(\mathbf{x})$ to denote whether the contact pattern $\mathbf{v}$ enables a node to retrieve enough packets to reconstruct data item d within the time constraint, given a replication solution $\mathbf{x}$. If the total number of packets of data item d that can be retrieved is equal to or larger than s, the data item can be reconstructed. Thus, $R_d^{\mathbf{v}}(\mathbf{x})$ can be calculated as below:

$$R_d^{\mathbf{v}}(\mathbf{x}) = \begin{cases} 1 & \sum_{j=1}^{N} \min(v_j, x_{j,d}) \geq s \\ 0 & otherwise. \end{cases} \tag{7}$$

Given that $\mathcal{N}$ and $\mathcal{M}$ denote the set of nodes and the set of data items respectively, the contact duration aware data replication problem can be re-defined as follows:

$$\max \sum_{d \in \mathcal{M}} \sum_{i \in \mathcal{N}} \sum_{\mathbf{v} \in \Phi} q_{i,d} P_i^{\mathbf{v}} R_d^{\mathbf{v}}(\mathbf{x}) \tag{8}$$

$$s.t.\ \forall i \in \mathcal{N}, \forall d \in \mathcal{M},\ x_{i,d} \in \{0, 1, \ldots, s\}, \tag{9}$$

$$\forall i \in \mathcal{N},\ \sum_{d \in \mathcal{M}} x_{i,d} \leq \rho_i, \tag{10}$$

$$\forall \mathbf{v} \in \Phi, \forall d \in \mathcal{M},\ R_d^{\mathbf{v}} \in \{0, 1\}, \tag{11}$$

$$\forall \mathbf{v} \in \Phi, \forall d \in \mathcal{M}, \sum_{j \in \mathcal{N}} \min(v_j, x_{j,d}) \geq s R_d^{\mathbf{v}}(\mathbf{x}). \tag{12}$$

Since the objective function to maximize is monotonically increasing with variable $R_d^{\mathbf{v}}$, constraint (11) and (12) ensure that $R_d^{\mathbf{v}}(\mathbf{x})$ equals to 1 if and only if $\sum_{j \in \mathcal{N}} \min(v_j, x_{j,d}) \geq s$; otherwise, $R_d^{\mathbf{v}}(\mathbf{x})$ equals to 0. However, the min function in the last constraint makes the optimization problem nonlinear. Therefore, we replace this constraint with the following constraints by introducing a set of auxiliary variables $h_{j,d}^{\mathbf{v}}(\mathbf{x})$:

$$\forall \mathbf{v} \in \Phi, \forall d \in \mathcal{M},\ \sum_{j \in \mathcal{N}} h_{j,d}^{\mathbf{v}}(\mathbf{x}) \geq s R_d^{\mathbf{v}}(\mathbf{x}), \tag{13}$$

$$\forall \mathbf{v} \in \Phi, \forall d \in \mathcal{M}, \forall j \in \mathcal{N},\ h_{j,d}^{\mathbf{v}}(\mathbf{x}) \leq v_j, \tag{14}$$

$$\forall \mathbf{v} \in \Phi, \forall d \in \mathcal{M}, \forall j \in \mathcal{N},\ h_{j,d}^{\mathbf{v}}(\mathbf{x}) \leq x_{j,d}. \tag{15}$$

where constraint (13), (14), and (15) are equivalent to constraint (12). In this way, the formulation turns to an MIP. It is easy to prove that this MIP formulation is equivalent to the formulation presented in Definition 1.

5.1.2 *Problem Analysis*

Traditional data-level replication problem can be reduced to the classical facility location problem, which has been proved to be NP-hard [5], [6]. Our packet-level replication problem is more complicated since it needs to determine not only what data items, but also how many packets of them to replicate at each node. We formulate the problem as an MIP which can be solved by the CPLEX optimization suite based on Branch and Bound. Branch and Bound algorithm solves optimization problems by implicit enumeration of the solution space, partitioning it into a search tree. Unfortunately, due to the integrity requirement, MIP problems are generally NP-hard, and in the worst case may require a search tree of exponential size. Our MIP problem is further complicated due to its exponential number of variables and constraints.

We use CPLEX to solve the problem in a small scale, and the results will be shown in Section 7 as a benchmark. However, if the network is large, it is hard to derive the optimal solution due to the extremely high computational complexity. To make data replication more applicable to the practical use, we further design a polynomial time distributed algorithm based on the local knowledge of each node, without using global knowledge such as the query rate of each node to each data item, the contact rate between any node pair, and the current replication placement of the whole network.

5.2 Distributed Data Replication Algorithm

Now we present our distributed contact Duration Aware Replication Algorithm (DARA).

5.2.1 *Main Idea*

DARA is a distributed algorithm run at each node. Based on node's local knowledge, DARA runs in a greedy manner, i.e., iteratively replicating the packet which brings the maximum replication benefit to other nodes, until the buffer is full. How to evaluate the replication benefit is the key to DARA. Intuitively, the benefit of replicating an additional packet of data item d into node i's buffer is affected by three factors: 1) the popularity of data item d, 2) the capability of node i to contribute the packet to others, and 3) the current availability of data item d. If the data item has high popularity and the node has large capability to contribute the packet to others, the replication benefit is large. However, if data item d can be retrieved at a high probability without this replication, the replication benefit will be lower. Although some of these factors have been implicitly considered in traditional replication and DTN routing algorithms [5], [28], they should be addressed differently when the contact duration limits are considered, especially for 2) and 3).

To obtain the popularity of data items, each node maintains a data popularity table which records the average query rate to each data item from its local view. Each node counts the number of pending requests it has received (including those generated by itself), and calculates the average query rate to each data item d as $q_d = n_d/n_{total}$, where n_d is the number of requests for data item d, and n_{total} is the total number of requests. The node updates the data popularity table at each time window as $q_d = q_d^{old}\alpha + q_d^{new}(1-\alpha)$, where q_d^{old} is the old query rate of data item d, and q_d^{new} is the new query rate derived in the latest time window. α is a decaying factor, which decides the weight of the old and new query rate.

Our goal is to maximize the average data retrieval probability. Thus, we use the retrieval probability to evaluate data availability. Each node maintains a data availability table which records the data retrieval probability of its contacted nodes to each data item. When two nodes contact, they exchange their data retrieval probability on each data item. To calculate the data retrieval probability, each node also maintains a data replication table, which records the replication placement of the contacted nodes. Based on the table, a node, say i, estimates its data retrieval probability to data item d as $P_{i,d} = \sum_{a=s-x_{i,d}}^{\infty} f_{A_i^d(\mathbf{x})}(a)$. $f_{A_i^d(\mathbf{x})}(a)$ can be derived via Eq. 5, and $f_{A_{i,j}^d(\mathbf{x})}(a)$ in Eq. 5 can be calculated as:

$$f_{A_{i,j}^d(\mathbf{x})}(a) = \begin{cases} P(V_{i,j}=a) & 0 \le a < x_{j,d} \\ \sum_{v=x_{j,d}}^{s} P(V_{i,j}=v) & a = x_{j,d} \\ 0 & otherwise. \end{cases} \tag{16}$$

To evaluate the capability of a node to contribute a packet to others, we define a metric called *replication benefit*. Next, we first introduce the concept of contribution and contribution gain, and then give the definition of replication benefit.

The contribution represents the capability of a node to contribute all its replicated packets to another node.

Definition 2. *The contribution that node i can provide to j in terms of data d, denoted as $C_{i,j}^d(x_{i,d})$, is defined as the expected number of packets of d that i can transmit to j within the time constraint,*

$$\begin{aligned} C_{i,j}^d(x_{i,d}) &= E\big(A_{j,i}^d(x_{i,d})\big) \\ &= \sum_{v=1}^{x_{i,d}-1} vP(V_{i,j}=v) + \sum_{v=x_{i,d}}^{s} x_{i,d}P(V_{i,j}=v). \end{aligned} \tag{17}$$

The contribution gain represents the increment in the contribution provided by a node by replicating an additional packet, which reflects the capability of the node to contribute the newly replicated packet to another node.

Definition 3. *For node i which has replicated $x_{i,d}$ packets of data item d, the contribution gain that it can provide to node j in terms of data item d is defined as:*

$$\begin{aligned} \Delta C_{i,j}^d(x_{i,d}) &= C_{i,j}^d(x_{i,d}+1) - C_{i,j}^d(x_{i,d}) \\ &= 1 - \sum_{v=0}^{x_{i,d}} P(V_{i,j}=v). \end{aligned} \tag{18}$$

Note that the contribution gain provided by a node to itself equals 1, since the node can directly enjoy its replicated data.

Now we define the replication benefit provided by replicating an additional packet of data item d to node i's buffer, which is determined by the popularity and availability of the data item, and the contribution gain that the node can provide to other nodes:

Definition 4. *The replication benefit provided by replicating an additional packet of data item d at node i which has already replicated $x_{i,d}$ packets of d can be defined as:*

$$B_{i,d}(x_{i,d}) = \begin{cases} \frac{q_d}{n}\sum_{j\in\mathcal{N}}(1-P_{j,d})\Delta C_{i,j}^d(x_{i,d}) & x_{i,d} < s \\ 0 & x_{i,d} = s. \end{cases}$$

where the replication benefit turns to zero if node i has already replicated s packets of data d. The derivation of q_d and $P_{j,d}$ are discussed earlier. The intuition behind Definition 4 is that the replication benefit provided by replicating a new packet of data d on node i should be the contribution gain (weighted by the popularity of d) that i can provide to other nodes if they currently cannot successfully retrieve d from the network.

5.2.2 The Protocol

In DARA, there are two cases for a node to download/replicate data: the node moves into the range of any AP or it contacts and swaps data with another node.

Node-to-AP. When a node moves into the wireless range of the AP, it iteratively replicates one packet of a chosen data item which can provide the maximum replication benefit, until no buffer space is left. More specifically, if node i has already replicated $x_{i,d}$ packets of data item d, the replication benefit of replicating an additional packet of the data item into the node is $B_{i,d}(x_{i,d})$. Node i downloads a packet of a chosen data item $d_{\max}$ which has the maximum $B_{i,d_{\max}}(x_{i,d_{\max}})$ among all the data items, from the AP.

When the buffer is full, the node still iteratively replicates one packet using the same rule of data selection, namely a packet of a chosen data item $d_{\max}$ with the maximum $B_{i,d_{\max}}(x_{i,d_{\max}})$ is downloaded. Meanwhile, to make room for the new packet, it needs to remove a packet that has the minimum replication benefit. Specifically, if node i has already replicated $x_{i,d}$ packets of data item d, removing any packet of the data will decrease the replication benefit by $B_{i,d}(x_{i,d}-1)$. Thus the node removes a packet of a chosen data item $d_{\min}$ with the minimum $B_{i,d_{\min}}(x_{i,d_{\min}}-1)$. This process iterates until $B_{i,d_{\max}}(x_{i,d_{\max}})$ is not larger than $B_{i,d_{\min}}(x_{i,d_{\min}}-1)$.

Node-to-Node. When two nodes contact, they can swap the data replicated in their buffer, and this data swap is controlled by the node with higher centrality value. Centrality metrics are widely used to measure the importance of the nodes in the network [9] [29]. However, the existing work only considers the contact frequency, and ignores the contact duration. In this paper, we use the expected number of packets which can be transmitted between the node to others within the time constraint as the centrality metric.

Definition 5. *The centrality value of node i is defined as:*

$$CEN_i = \frac{1}{n-1} \sum_{j \in \mathcal{N}, j \neq i} \sum_{v=1}^{s} vP(V_{i,j} = v). \tag{19}$$

The node with higher centrality is referred to as the *master*, and the node with lower centrality is referred to as the *slave*. The master downloads data from the slave according to the same rule used in the Node-to-AP case, until the connection is over or there is no suitable data to be downloaded from the slave. The only difference is that the master needs to send the packets that are replaced by the newly downloaded packets back to the slave. The slave replicates them, and removes the packets which have been sent to the master. Thus, no redundant coded packet is generated. The two nodes just swap some data to increase the replication benefit of the master. Note that although swapping data by considering the replication benefit of both nodes is more beneficial, it requires more time-consuming information exchanges for coordination, which may not fit the contact duration limited scenario.

Discussions. DARA has two types of cost: one is the computation cost for encoding and decoding, and the other is the communication cost for exchanging metadata (e.g., the data retrieval probability to each data item) when two nodes contact. Generally speaking, the metadata is much smaller than the actual data item, so the communication cost has minimal effect on the performance.

It is difficult to derive the performance bound due to the following reasons. In DARA, the replication placement of a node depends on the node's local knowledge of the average query rate to each data item and the replication placement of other nodes. Due to communication delay, the same knowledge is not shared across all nodes in the network. This knowledge also keeps being updated as other nodes replicate new packets. The uncertainty of such knowledge makes it difficult to predict the replication placement and estimate the performance of DARA. Alternatively, we compare its performance to the optimal solution in the evaluations (Section 7.2.1).

6 Contact Duration Aware Data Replication: The Licensed Spectrum Case

In this section, we first formulate the contact duration aware data replication problem under the licensed spectrum case and then propose a practical algorithm which operates in a fully distributed manner.

6.1 Problem Formulation and Analysis

We first describe the system models and then formulate a mixed integer programming problem.

6.1.1 System Models

With cognitive radio techniques, mobile devices can opportunistically use the licensed spectrum (e.g., TV channels) for data transmission. Since they do not have license to operate on these channels, their data transmission should not interfere with licensed users. That is, they have to vacate the channels when they is accessed by the *primary users* who are licensed to access the channels. Mobile devices at different regions are affected the primary users at that area, so they generally have different number of channels available for data transmission and hence have different data transmission capacity. The node contact model in the unlicensed spectrum case does not consider where the contact happens, so it cannot be used here. To address this problem, we introduce the following models for node movement and primary user appearance.

Node movement. Following existing works [30], [31], [32], the movement of a node i is modeled by a discrete-time Markov chain H_i^t, whose states are represented by the locations (the entire area can be divided into a set of grids and each grid defines a location). The set of locations is denoted by $\mathcal{L} = \{1, , L\}$. We use $\lambda_i^{l,l'}$ to denote the probability of node i to make transition from location l to location l'.

Primary user appearance. There are C channels, which may be sometimes accessed by primary users. The set of channels is denoted by $\mathcal{C} = \{1, , C\}$. Each location is affected by a number of primary users on each channel. Let $I_{l,c}^t$ denote the availability of channel c at location l at time t. That is, $I_{l,c}^t$ is 1 if channel c is available for (unlicensed) mobile users at location l at time t (not accessed by primary users); otherwise, $I_{l,c}^t$ is 0. Based on existing works [33], [34], [35], we assume $I_{l,c}^t$ follows a discrete-time Markov chain with two states 0, 1, and use $\omega_{l,c}^{b,b'}$ to denote the probability of $I_{l,c}^t$ to make transition from state b to state b'.

If two nodes are at location l at the same time t, the total amount of data that can be transmitted between them at time t is $\beta(\sum_{c \in \mathcal{C}} I_{l,c}^t)$. Here β denotes the channel bandwidth, i.e., the total amount of data that can be transmitted per channel. We assume all channels have equal bandwidth, and a node can use multiple channels for transmission at the same time. In practice, such flexibility in using multiple channels can be achieved by k-agile software-defined radios [36].

Note that our system does not assume that both the licensed and unlicensed bands are used at the same time. The major concern is that the licensed spectrum (such as the whitespace channels in the 400-700 MHz range) can have longer signal propagation characteristics than the unlicensed spectrum (such as the WiFi channels around 2.4 GHz). Our system model assumes all channels have similar propagation characteristics, in order to facilitate the calculation of data transmission capacity upon contact. How to perform data replication with channels of vastly different propagation characteristics needs further study, and will be left as our future work.

6.1.2 MIP Formulation

Let $\mathcal{H}$ represent the set of all possible patterns of node movement. Each element $H \in \mathcal{H}$ is denoted by an $N \times T$ vector $(H_i^t)_{N \times T}$, where H_i^t denotes the location at which node i is located at time t.

Let $\mathcal{I}$ represent the set of all possible patterns of primary user appearance. Each element $I \in \mathcal{I}$ is denoted by an $L \times C \times T$ vector $(I_{l,c}^t)_{L \times C \times T}$, where $I_{l,c}^t$ denotes the availability of channel c at location l at time t.

Let Λ_H denote the probability that the node movement follows pattern H, and Ω_I denote the probability that the primary user appearance follows pattern I. Here we assume the availability of different channels at each location is independent, and the channel availability at different locations is independent. Then, Λ_X and Ω_I can be calculated as $\prod_{i\in\mathcal{N}}\prod_{t=1}^{T}\lambda_i^{H_i^{t-1},H_i^t}$ and $\prod_{l\in\mathcal{L}}\prod_{c\in\mathcal{C}}\prod_{t=1}^{T}\omega_{l,c}^{I_{l,c}^{t-1},I_{l,c}^t}$ respectively.

Let $R_{i,d}^{H,I}(\mathbf{x})$ denote whether node i can retrieve enough coded packets (at least s packets) to reconstruct data item d within the time constraint, given node movement pattern H, primary user appearance pattern I, and replication solution $\mathbf{x}$. $R_{i,d}^{H,I}(\mathbf{x})$ can be calculated as follows:

$$R_{i,d}^{H,I}(\mathbf{x}) = \begin{cases} 1 & \sum_{j\in\mathcal{N}}\min\left(x_{j,d},\frac{1}{g}U_{i,j}^{H,I}\right)\geq s \\ 0 & \text{otherwise,} \end{cases} \tag{20}$$

where $U_{i,j}^{H,I}$ is the amount of data that can be transmitted from node i to node j within the time constraint, given node movement pattern H and primary user appearance pattern I. Note that the number of packets of data item d that can be transmitted from node j to node i should be bounded by $x_{j,d}$ (the number of packets of data item d that are replicated by node j). $U_{i,j}^{H,I}$ can be calculated as $\beta\sum_{t=1}^{T}\sum_{l\in\mathcal{L}}\sum_{c\in\mathcal{C}}I_{l,c}^tF_{H_i^t,H_j^t}$, where $I_{l,c}^t$ denotes the availability of channel c at location l at time t, and $F_{H_i^t,H_j^t}$ is an indicator function. If $H_i^t=H_j^t$, $F_{H_i^t,H_j^t}=1$; otherwise, $F_{H_i^t,H_j^t}=0$.

The contact duration aware data replication problem can be re-defined as follows:

$$\max \sum_{d\in\mathcal{M}}\sum_{i\in\mathcal{N}}\sum_{H\in\mathcal{H}}\sum_{I\in\mathcal{I}} q_{i,d}\Lambda_H\Omega_I R_{i,d}^{H,I}(\mathbf{x}) \tag{21}$$

$$s.t. \quad \forall i\in\mathcal{N},\forall d\in\mathcal{M}, x_{i,d}\in\{0,,s\}, \tag{22}$$

$$\forall i\in\mathcal{N},\sum_{d\in\mathcal{M}}x_{i,d}\leq\rho_i, \tag{23}$$

$$\begin{aligned}&\forall d\in\mathcal{M},\forall i\in\mathcal{N},\forall H\in\mathcal{H},\forall I\in\mathcal{I}:\\ &R_{i,d}^{H,I}(\mathbf{x})\in\{0,1\},\end{aligned} \tag{24}$$

$$\sum_{j\in\mathcal{N}}\min\left(x_{j,d},\frac{1}{g}U_{i,j}^{H,I}\right)\geq sR_{i,d}^{H,I}(\mathbf{x}). \tag{25}$$

Following the techniques mentioned in Section 5.1.1, we introduce a set of auxiliary variables $h_{i,j,d}^{H,I}(\mathbf{x})$ to make constraint (25) linear. Now the problem becomes a mixed integer programming problem.

This problem is much more complicated than the unlicensed spectrum case, due to its exponential number of variables (constraints). For example, since $\mathcal{H}$ and $\mathcal{I}$ have $L^{N\times T}$ elements and $2^{L\times C\times T}$ elements respectively, the number of variables $h_{i,j,d}^{H,I}(\mathbf{x})$ is $N^2ML^{N\times T}2^{L\times C\times T}$. Even for a small sized problem with $N=10$, $M=10$, $L=5$, $C=10$, $T=50$, the number is 1.15×10^{1105}, which is too big to be loaded into general computer memory by any optimization software (e.g., CPLEX). To address this challenge, we will propose a practical algorithm to reduce the computational complexity.

6.2 Distributed Data Replication Algorithm

Now we present our distributed algorithm which is both spectrum aware and contact duration aware (spectrum-aware DARA). Similar to the unlicensed spectrum case, each node greedily replicates the packet that brings the maximum replication benefit until the storage is full. The only difference is the evaluation of replication benefit. In this case, the calculation of data retrieval probability of data item d (i.e., $P_{j,d}$) in Definition 4 becomes even more difficult with the consideration of primary user appearance. Thus, we redefine the replication benefit as follows to reduce the computational complexity.

Definition 6 (Licensed Spectrum Case). *The replication benefit provided by replicating an additional packet of data item d at node i which has already replicated $x_{i,d}$ packets of d can be defined as:*

$$B_{i,d}(x_{i,d})=\sum_{j\in\mathcal{N}}q_{j,d}\Delta C_{i,j}^d(x_{i,d}). \tag{26}$$

Here the contribution gain $\Delta C_{i,j}^d(x_{i,d})$ is obtained from $P(V_{i,j}=v)$, where $V_{i,j}$ is the maximum number of packets that can be transmitted between nodes i and j within the time constraint. We calculate $V_{i,j}$ as follows based on the stationary distribution related to node movement and primary user appearance.

In general, $\lim_{t\to\infty}P(H_i^t=l|H_i^0=l')$ ($\lim_{t\to\infty}P(I_{l,c}^t=b|I_{l,c}^0=b')$) exists and is independent of l' (b'). It is denoted by $\tilde{\lambda}_i^l$ ($\tilde{\omega}_{l,c}^b$), which can be solved by

$$\begin{cases}\tilde{\lambda}_i^l=\sum_{l'\in\mathcal{L}}\lambda_i^{l',l}\tilde{\lambda}_i^{l'},\forall l\in\mathcal{L}\\ \sum_{l\in\mathcal{L}}\tilde{\lambda}_i^l=1\end{cases} \tag{27}$$

$$\begin{cases}\tilde{\omega}_{l,c}^b=\sum_{b'\in\{0,1\}}\omega_{l,c}^{b',b}\tilde{\omega}_{l,c}^{b'},\forall b\in\{0,1\}\\ \sum_{b\in\{0,1\}}\tilde{\omega}_{l,c}^b=1.\end{cases} \tag{28}$$

If t is large enough, $P(H_i^t=l)$ ($P(I_{l,c}^t=b)$) will be very close to the probability $\tilde{\lambda}_i^l$ ($\tilde{\omega}_{l,c}^b$). In delay tolerant networks, the time constraint is usually loose (i.e., t is usually large), so we can use $\tilde{\lambda}_i^l$ ($\tilde{\omega}_{l,c}^b$) to approximate $P(H_i^t=l)$ ($P(I_{l,c}^t=b)$). Then the expected amount of data that can be transmitted from node i to node j within the time constraint is approximated by $\beta T\sum_{l\in\mathcal{L}}\sum_{c\in\mathcal{C}}\tilde{\lambda}_i^l\tilde{\lambda}_j^l\tilde{\omega}_{l,c}^1$. Based on Eq. (6), the maximum number of packets that can be transmitted between nodes i and j within the time constraint (i.e., $V_{i,j}$) will be obtained.

7 Performance Evaluation

In this section, we evaluate the performance of DARA on both synthetic and realistic traces. We first show the unlicensed spectrum case and then show the licensed spectrum case.

7.1 Schemes for Comparison

To evaluate the performance of DARA, we compare it with eight replication schemes: 1. **OPT**: The optimal solution

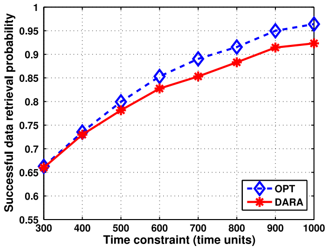
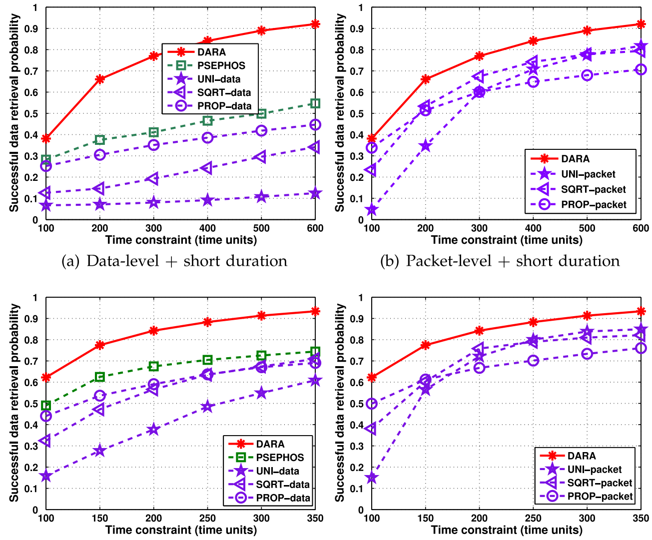


Fig. 3. Comparison of DARA and the optimal solution.



(a) Data-level + short duration (b) Packet-level + short duration

(c) Data-level + long duration (d) Packet-level + long duration

Fig. 4. Comparison of DARA and other schemes on the synthetic traces.

derived from the MIP formulation using CPLEX; 2. **PSEPHOS**: An existing data-level replication scheme in DTNs [12]; 3. **UNI-data** (4. **UNI-packet**): A data-level (packet-level) replication scheme, where the storage space is evenly allocated among all data items; 5. **SQRT-data** (6. **SQRT-packet**): A data-level (packet-level) replication scheme, where the storage allocation is proportional to the square root of the query rate; 7. **PROP-data** (8. **PROP-packet**): A data-level (packet-level) replication scheme, where the storage allocation is proportional to the query rate. We also evaluate the performance of spectrum-aware DARA when licensed channels are used.

In PSEPHOS, each node maintains a "vote" for each data item based on the information collected from others to rate the caching importance of the data item. Whenever a node meets the AP, it downloads the data with the top votes. However, this scheme ignores the contact duration limits, and replicates at data-level. The other six naive schemes are designed for comparison purpose. These schemes only consider the popularity of the data items, and replicate data items according to three typical replication rules: *uniform*, *square root*, and *proportional*. Under the same rule, the total number of buffers allocated to each data item remains unchanged between the data-level and packet-level schemes. The difference is that in data-level scheme, a node either replicates a complete data item, or does not replicate any packet of it, but in packet-level scheme, by adopting erasure coding each data item is more evenly allocated among the nodes, and every node only replicates parts of it.

7.2 The Unlicensed Spectrum Case

7.2.1 Synthetic Traces

Simulation settings. We generate a small-scale trace and a large-scale trace. In the small-scale trace (large-scale trace, resp.), there are 10 (100, resp.) mobile nodes and 10 (50, resp.) data items in the network. Each data item contains 8 (32, resp.) packets, and each node has storage of size 24 (96, resp.). In both traces, the contact rates between node pairs are randomly generated within the range of $[0.0003, 0.005]$. The contact duration is randomly generated following the Pareto distribution, where each node pair has its distinct shape and scale parameters of the distribution. The shape and scale parameters are within the range of $[2, 4]$ and $[1, 3]$ respectively, and then the expected number of packets that can be sent during a contact between a node pair is within the range of $[1.33, 6]$.[1] To show the impact of contact duration, in the large-scale trace, we further generate a long contact duration scenario, where the shape and scale parameters are set within the range of $[1, 1.5]$ and $[5, 10]$ respectively, and hence the expected number of packets that can be transmitted during a contact between a node pair is within the range of $[15, \infty)$.

In both traces, we also add a static node to act as the AP, from which the mobile nodes can download and replicate data. The contact frequency between the AP and the mobile nodes is randomly generated within the range of $[0.0001, 0.001]$. We set the contact frequency low enough so that the mobile nodes prefer to retrieve data from other peers rather than wait for the contact opportunities with AP. We use the Zipf-like query distribution, where the query rate of the ith most popular data item is proportional to i^{-w}, and w is set to 1 unless specified differently. We sort the data items in the decreasing order of its popularity, and number them from 1 to m. In each simulation run, the first $1/5$ of the trace is used for warmup. The presented results are averaged over 10 runs.

Comparisons to the optimal solution. First, we compare the performance of DARA to the optimal solution derived from the MIP formulation. Due to the extremely high computational complexity of solving MIP, we compare the two schemes using the small-scale trace. Fig. 3 compares the data retrieval probability of the two schemes when the time constraint varies from 300 to $1,000$ time units. As can be seen from the figure, DARA achieves close performance to the optimal solution without relying on the global knowledge and without suffering from the high computational complexity.

Comparisons to other replication schemes. In this section, we use the large-scale trace to evaluate the performance of DARA against seven other schemes, which are divided into two groups: data-level (including UNI-data, SQRT-data, PROP-data, and PSEPHOS) and packet-level (including UNI-packet, SQRT-packet, and PROP-packet). As shown in Figs. 4a and 4b, in the scenario of short contact duration, the successful data retrieval probability in the packet-level schemes is much higher than that in the data-level schemes,

1. $\frac{\tau_{i,j} y_{i,j}}{\tau_{i,j}-1}$ is the expected number of packets that can be transmitted between node i and node j, where $\tau_{i,j}$ and $y_{i,j}$ are the shape and scale parameter.

especially when the time constraint becomes loose. The reason is that packet-level replication schemes can better exploit the contact opportunities. The coded packets of a data item are more evenly allocated among the nodes, which increases the number of potential sources from which a requester can obtain packets. When the time constraint becomes looser, the data requester has more contact opportunities with the nodes replicating the packets. On the contrary, in data-level replication schemes, data packets are replicated in a few hot-spot nodes. The probability to contact those nodes is small, and even the contact happens, it is hard for those nodes to send out all the packets to the requester during a short contact. Thus, lots of contact opportunities are wasted which significantly reduces the successful data retrieval probability.

As shown in Fig. 4a, compared to PSEPHOS, UNI-data, SQRT-data, and PROP-data, DARA improves the successful data retrieval probability by 35.1, 468.9, 202.5 and 51.2 percent respectively when the time constraint is 100. Such improvement changes to 68.4, 639.3, 169.6 and 106.1 percent when the time constraint reaches 600. Among the data-level replication schemes, PSEPHOS performs the best, since it considers the node contact patterns, while the other three naive data-level schemes treat all nodes equally.

From Fig. 4a, it is clear to see that PROP-data performs the best and UNI-data performs the worst among the three naive data-level schemes. However, as shown in Fig. 4b, among the three naive packet-level schemes, no scheme is obviously better than others. When the time constraint is smaller than 200, PROP-packet performs the best. This is because short time constraint requires for larger replication factor and PROP-packet can at least ensure higher retrieval probability for popular data. When the time constraint is larger than 500, even lower replication factor can ensure good performance, and thus UNI-packet achieves the best performance among the three, where every data item can be allocated with almost enough storage. However, PROP-packet gives too much weight to popular data, which wastes the storage space. Among the three, SQRT-packet achieves the best performance when the time constraint is within the range of $[200, 500]$, since its replication strategy is a trade-off between UNI-packet and PROP-packet. These three packet-level schemes allocate storage only according to the data popularity. Since DARA considers both node contact pattern and data availability, it always has the best performance. Compared to UNI-packet, SQRT-packet, PROP-packet, DARA improves the successful data retrieval probability by 710.4, 62.4, and 12.7 percent with time constraint 100. When the time constraint reaches 600, the improvement changes to 12.5, 16.0, and 30.2 percent.

In the scenario of long contact duration, the performance of packet-level replication schemes has no significant improvement compared to data-level replication schemes as shown in Figs. 4c and 4d. When the time constraint is short (within the range of $[100, 150]$), some data-level schemes such as PSEPHOS even have better performance than naive packet-level schemes. Within short time constraint, the contact opportunities between the data requesters and others are rare, and in the scenario of long contact duration, the expected number of packets can be transmitted during a contact tends to be large. The naive packet-level schemes let the nodes only replicate parts of the data items, which may waste the precious contact opportunities if the contact durations happen to be long. When the time constraint becomes loose (within the range of $[200, 350]$), the naive packet-level schemes have better performance. Since the data requesters have more contact opportunities with others, the packet-level schemes which replicate data more evenly among the nodes can make better use of these opportunities. Compared to the seven schemes, DARA still achieves the best performance in the scenario of long contact duration.

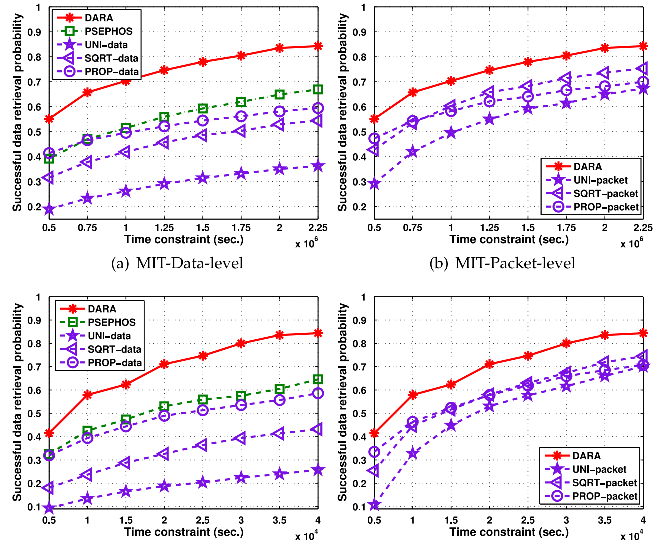
Discussion on the impact of the number of mobile users. Generally speaking, the successful data retrieval probability increases as the number of mobile users increases. For the data requester, since more nodes are contacted, it becomes more likely to download the complete data within the time constraint. This is demonstrated by comparing the simulation result of small-scale trace (10 mobile users) with that of large-scale trace (100 mobile users). For example, when the time constraint is 300, the successful data retrieval probability of the large-scale trace is 0.77 (as shown in Fig. 4a), while the successful data retrieval probability of the small-scale trace is only 0.66 (as shown in Fig. 3). Note that in our simulation settings, the number of packets for reconstructing the complete data item is set larger in the large-scale trace (32) than in the small-scale trace (8). If such difference does not exist, the successful data retrieval probability of the large-scale trace must be even higher.

7.2.2 Realistic Traces

Simulation settings. We further evaluate the performance of DARA using two realistic traces: *MIT Reality* [37] and *Infocom05* [38]. The MIT Reality trace was collected by using 97 Nokia 6600 smartphones which were carried by staffs and students at MIT over nine months, and the Infocom05 trace was collected by using 41 iMotes which were carried by the participants of conference Infocom05 over three days. The mobile devices sense each other using Bluetooth and update the contact log at an interval of 300 seconds for MIT Reality trace and 120 seconds for Infocom05 trace. Due to the coarse granularity of the traces, there are many contact records whose contact duration is zero. In the evaluation, we set the sensing interval to be the time unit of transmitting one packet. If the contact duration is zero, we assume that only one packet can be transmitted during the contact.

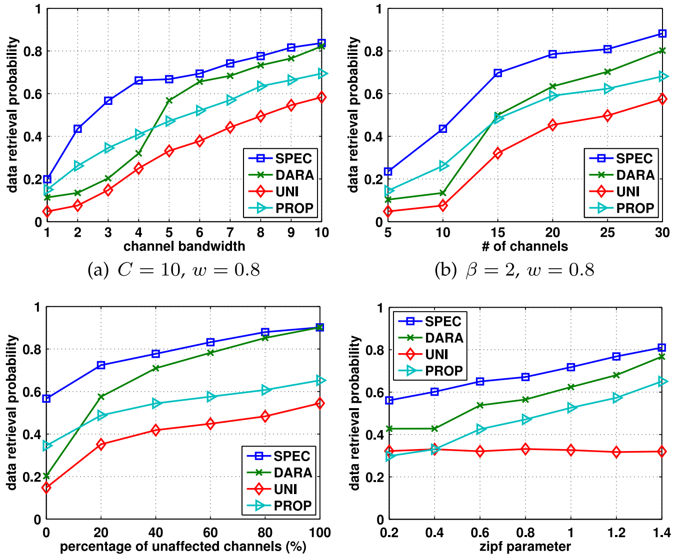
In the MIT Reality trace (Infocom05 trace, resp.), we set 30 (40, resp.) data items in the network, and each data item contains 64 (32, resp.) packets. Every node has the storage buffer of 128 (96, resp.). We also add a virtual static node to act as the AP. The contact frequency between the AP and mobile nodes is randomly generated within the range of $[2 \times 10^{-7}, 6 \times 10^{-7}]$ and $[8 \times 10^{-6}, 2 \times 10^{-5}]$ in the MIT Reality and the Infocom05 trace, respectively. In each simulation run, the first $1/3$ of the trace is used for warmup. The presented results are averaged over 10 runs.

Results. Fig. 5 compares the data retrieval probability of DARA to seven other schemes on both the MIT Reality and the Infocom05 trace. As can be seen, packet-level schemes outperform data-level schemes on both traces. Among the three replication strategies: uniform, square-root and



(a) MIT-Data-level (b) MIT-Packet-level (c) Infocom05-Data-level (d) Infocom05-Packet-level

Fig. 5. Comparison of DARA and other schemes on the realistic traces.



(a) $C = 10$, $w = 0.8$ (b) $\beta = 2$, $w = 0.8$ (c) $\beta = 3$, $C = 10$, $w = 0.8$ (d) $\beta = 5$, $C = 10$

Fig. 6. Comparison of SPEC and other schemes on the synthetic trace.

proportional, the uniform strategy performs the worst in both packet-level and data-level schemes, on both traces. The low contact frequency of the trace demands for relatively large replication factor. Since the uniform replication strategy sets equal priority to different data items, most data items are not allocated with enough buffers to ensure high data retrieval probability.

Among data-level replication schemes, PSEPHOS performs the best since it considers different contact patterns of the nodes. Compared to PSEPHOS, DARA improves the successful data retrieval probability by about 33.3 and 33.8 percent on the MIT Reality and the Infocom05 trace, respectively. Among the naive packet-level replication schemes, SQRT-packet outperforms others in a wide range of time constraint. Compared to it, DARA also improves the successful data retrieval probability by about 15.4 and 25.3 percent on the MIT Reality and the Infocom05 trace, respectively.

7.3 The Licensed Spectrum Case

We compare four packet-level replication schemes: **SPEC** (i.e., spectrum-aware DARA), **DARA**, **UNI** (i.e., UNI-packet) and **PROP** (i.e., PROP-packet).

7.3.1 Synthetic Traces

Simulation settings. We generate a synthetic trace in which there are 20 mobile nodes and 20 data items in the network. We set 20 locations, and the channel availability at each location is determined by our model for primary user appearance (the transition probabilities among different states are randomly generated). Considering that the node moving speed is relatively slow, we assume it takes 100 time units to make transition from one location to another. Each data item is generated by some node which is randomly selected, and can be reconstructed by 20 coded packets. In our simulations, we assume each node has equal storage space and can replicate at most 100 coded packets. The data query pattern is based on Zipf-like distribution in which the query rate of the ith most popular data item is proportional to i^{-w}. Here w shows how skewed the query pattern is, and is set to 0.8 unless specified differently.

We vary the *channel bandwidth* (β), the *number of channels* (C), and the *Zipf parameter* (w), to study their effects on the (average) data retrieval probability. We also investigate the effect of primary user appearance on the performance. Specifically, we select some channels and make them unaffected by primary users, in order to study how the percentage of these channels affects the data retrieval probability. In all simulations, the first half of the trace is used for warmup to collect necessary network information. All the data and queries are generated during the second half of the trace. The presented results are averaged over 100 runs.

Results. Fig. 6a shows the effect of channel bandwidth on the data retrieval probability. For all schemes, the data retrieval probability increases as the channel bandwidth increases, since more packets can be transmitted upon contact. Among the four schemes, SPEC performs the best, since it considers the effect of primary user appearance on the data replication strategy, which is ignored by the other three schemes. Compared to DARA, UNI and PROP, SPEC improves the data retrieval probability by 75, 318 and 32 percent when the channel bandwidth is one packet per time unit. When the channel bandwidth reaches 10 packets per time unit, the improvement changes to 2, 44 and 21 percent.

When the channel bandwidth is less than five packets per time unit, PROP performs the best among the other three schemes. PROP outperforms UNI since PROP allocates more storage space to the data items of high query rate. PROP outperforms DARA due to the following reason. The replication strategy in DARA is based on the data transmission capacity upon each contact. Without considering the primary user appearance, the data transmission capacity cannot be calculated accurately, which affects the performance of DARA. When the channel bandwidth exceeds five packets per time unit, DARA outperforms PROP. Increasing the channel bandwidth makes data replication less restricted by the data transmission capacity upon each contact. This reduces the effect of inaccurate calculation of data transmission capacity on the performance of DARA. Meanwhile, DARA considers the node contact pattern which is not considered in PROP, and thus DARA performs better.

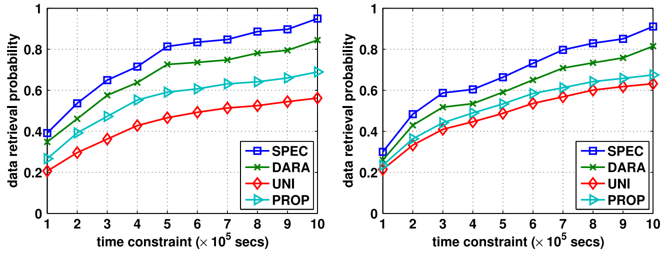
Fig. 6b shows the effect of the number of channels on the data retrieval probability. For all schemes, the data retrieval probability increases as the number of channels increases, since there are generally more available channels to be used for data transmission upon contact. When there are 10 channels in the network (the channel bandwidth $\beta = 3$), Fig. 6c shows the effect of primary user appearance on the data retrieval probability. For all schemes, the data retrieval probability increases as more channels are unaffected by primary users, since more packets can be transmitted upon contact by using more available channels. When all channels are unaffected, DARA and SPEC have the same data retrieval probability of 90 percent since data replication is only determined by the node contact pattern.

Fig. 6d shows the effect of Zipf parameter w on the data retrieval probability. For SPEC, DARA and PROP, the data retrieval probability increases as w increases. Increasing w makes the query pattern much skewer, which increases the query rate of popular data items. These three schemes generally replicate more packets of popular data items, so their data retrieval probability increases. For UNI, the performance is similar to that of PROP when the Zipf parameter is 0.2 or 0.4. Small w indicates similar query rate for all data items, so the replication strategy of UNI is similar to that of PROP. When w increases, the popular data items are given higher query rate, but are not treated differently in UNI. Thus, the data retrieval probability of UNI almost stays flat at around 32 percent with the increase of w.

7.3.2 Realistic Traces

Simulation settings. The performance of our scheme is also evaluated on realistic traces. However, most realistic traces are inappropriate for our simulations. They do not record where each contact happens, and hence it is difficult to model the channel availability upon each contact. We find that in the Dartmouth trace [30] and the UCSD trace [39], each mobile node records the nearby associated wireless access points, which can be used to model the locations. A contact happens if two nodes are at the same location at the same time. The amount of data that can be transmitted upon contact depends on the channel availability at that location, which can be simulated using our model for primary user appearance (the transition probabilities among different states are randomly generated).

The Dartmouth trace was collected by several thousand wireless laptops which were carried by students and faculty at the Dartmouth College campus over five years. In our simulation, we focus on the data collected between September 1, 2002 and December 1, 2002. If two nodes are associated with the APs in the same building, they are assumed to be at the same location. There are 185 locations in total by grouping APs of the same building together. We sort all users in a descending order of trace length, and select the first 50 users for simulation. We set 20 channels and 20 data items. The channel bandwidth is five packets per second.



(a) Dartmouth trace (b) UCSD trace

Fig. 7. The effects of time constraint.

Each data item is generated by some node which is randomly selected, and can be reconstructed by 20 coded packets. The storage space of each node is the combined size of five data items. The data query pattern is based on Zipf-like distribution with $w = 0.8$.

The UCSD trace was collected by approximately 300 wireless PDAs which were carried by UCSD freshmen for an 11-week period between September 22, 2002 and December 8, 2002. There are 520 APs, and each AP corresponds to one location. Similar to the Dartmouth trace, we sort all users in an descending order of trace length, and select the first 50 users for simulation. The other simulation settings are the same as the Dartmouth trace.

In both Dartmouth trace and UCSD trace, we vary the time constraint to study its effect on the (average) data retrieval probability. In all simulations, the first half of the trace is used for warmup to collect necessary network information. All the data and queries are generated during the second half of the trace. The presented results are averaged over 20 runs.

Results. Fig. 7 shows the effect of time constraint on the data retrieval probability on the Dartmouth trace and the UCSD trace, respectively. For all schemes, the data retrieval probability increases as the time constraint increases. This is because increasing the time constraint creates more contact opportunities to retrieve the requested data items. Among the four schemes, SPEC performs the best, since it considers the effect of primary user appearance on the data replication strategy, which is ignored by the other three schemes. Compared to DARA, UNI and PROP, SPEC improves the data retrieval probability by 12, 90, 47 percent for Dartmouth trace (15, 40, 28 percent for UCSD trace) with time constraint 10^5secs. When the time constraint reaches 10^6secs, the improvement changes to 12, 69, 38 percent for Dartmouth trace (12, 44, 35 percent for UCSD trace).

8 Conclusions

In this paper, we studied the impacts of contact duration limitation on data replication in DTNs and further studied how to perform data replication when mobile users operate on the under-utilized licensed spectrum. Different from traditional data-level replication schemes, we replicate data at packet-level and address the problems of which data items to replicate and how many packets of each data item to replicate at each node. Our study consists of two cases based on the operating channels: unlicensed channels and licensed channels. For both cases, we formulated the contact duration aware data replication problem as a mixed integer programming problem and designed a distributed scheme to replicate data according to a novel "replication benefit" metric, which is determined by the capability of a node to contribute the newly replicated packet to others. Extensive simulations based on synthetic and realistic traces show that our solution outperforms other replication schemes in terms of successful data retrieval probability in various scenarios.

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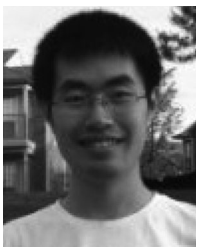

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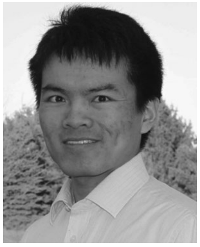

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