Multi-Copy Data Dissemination with Probabilistic Delay Constraint in Mobile Opportunistic Device-to-Device Networks

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***Abstract*—Device-to-device (D2D) is a new paradigm that enhances network performance by offering a wide variety of advantages over traditional cellular networks, e.g., efficient spectral usage and extended network coverage. Efficient data dissemination is indispensable for supporting many D2D applications such as content distribution and location-aware advertisement. In this work, we study the problem of multi-copy data dissemination with probabilistic delay constraint in mobile opportunistic D2D networks. We first formally formulate the problem and introduce a centralized heuristic algorithm which aims to discover a graph for multicasting, in order to meet delay constraint and achieve low communication cost. While the centralized solution can be adapted to a distributed implementation, it is inefficient in a mobile opportunistic D2D network, since it intends to apply a deterministic transmission strategy in a nondeterministic network by delivering all data packets via a predetermined route. Based on such observation, we develop a distributed online algorithm based on the optimal stopping strategy that makes an efficient decision on every transmission opportunity. Extensive simulations under real-world traces and random walk mobility model are carried out to learn the performance trend of the proposed schemes under various network settings.**

I. Introduction

To meet a thousand-fold increase in mobile and wireless traffic volume over the next decade, millimeter-wave communication has been identified as a promising technology for future 5G cellular networks which are responsible for improving spectrum utilization and energy efficiency. However, it brings a set of unique technical challenges such as severe path loss and undesired coverage holes. To this end, device-to-device (D2D) communication has added a new dimension to improve network efficiency and reliability. This paper focuses on mobile opportunistic D2D networks that do not depend on any infrastructure but, instead, exploit opportunistic connections between mobile devices to enable device-to-device communication. Mobile opportunistic D2D networks are characterized by intermittent and nondeterministic connectivity, often due to interruptible wireless links, sparse network deployment and/or nodal mobility. It seems that D2D just resembles another scenario of opportunistic networking discussed in the context of delay/disruption-tolerant networks [1]–[3], sporadically connected sensor networks [4]–[6], vehicular networks [7]–[9], and peer-to-peer mobile social networks [10]–[17]. However, there are a set of new challenges to be addressed, primarily driven by the emerging D2D-based applications.

D2D networks gain significant value by serving as a supplement and augment to the infrastructure based B2D (i.e., base-station-to-device) communication by effectively supporting general communication needs of mobile users (especially for real-time voice and data delivery). One one hand, D2D helps discover and update social links that are not captured by B2D communication. For example, two people may go to the same downtown amphitheatre around the same time every weekend for outdoor music shows. But they have never talked to each other, neither do they have an overlap between their online social communities. Such relation can be discovered by D2D, which subsequently suggests a possible social link. On the other hand, efficient data dissemination with minimal or no supervision of centralized coordinator is indispensable for supporting D2D applications, such as video file and large data file transfer [18]. While data dissemination in D2D is subject to long delay due to its intermittent connectivity, it is highly desired not only for its cost benefit but also for its effectiveness, since the interaction between mobile users is closely correlated to their social groups and behaviors, offering great opportunities to deliver data to the target audience.

The contribution of this work is given below. We first introduce a binary transmission vector for the delay-constrained multi-copy multi-path least-cost multicast problem. Then we propose a centralized heuristic algorithm which aims to discover a graph for multicasting, in order to meet delay constraint and achieve low communication cost. While the centralized solution can be adapted to a distributed implementation, *it is inefficient in a mobile opportunistic network, since it is not only computationally expensive but also intends to apply a deterministic transmission strategy in a nondeterministic network* by transmitting all data packets via a predetermined route. In mobile opportunistic networks, even if the optimal routing graph can be computed, it is the "best" only on a statistic basis for a large number of data packets. It is not necessarily the best solution for every individual transmission. Based on the above observation, we develop a distributed

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online algorithm based on the optimal stopping strategy that makes an efficient decision on every transmission opportunity. We carry out simulations under real-world traces and random walk mobility model to evaluate the scalability of the proposed schemes under various network settings.

The rest of the paper is organized as follows: Sec. II discusses related work. Sec. III formulates the problem. Sec. IV presents the centralized heuristic algorithm. Sec. V introduces the distributed online solution. Sec. VI presents large-scale simulations under real-world mobility traces and random walk mobility model. Finally, Sec. VII concludes the paper.

II. Related Work

Data dissemination is essentially a multicasting problem. While there are a handful of studies on multicasting in mobile opportunistic networks or traditional delay tolerant networks [19]–[25], they all deal with unconstrained, best-effort data transmissions. Note that although delay is often considered as a metric in performance evaluation, none of the existing solutions formulate the problem with an explicit delay constraint. On the other hand, a series of approaches have been developed for single-copy routing in mobile opportunistic networks [12], [26], [27]. However, those approaches are vulnerable in mobile opportunistic networks given the non-deterministic and intermittent connectivity settings, because they may frequently fail to identify only one single path that meets delay constraint. Data dissemination in D2D is a fairly new area with limited existing solutions [28]–[32]. [28] proposes DataSpotting, a system that explores the feasibility of offloading cellular traffic via D2D content transfer. [29] develops a compressed hybrid automatic repeat request (HARQ) mechanism for the reliable multicast services in the cellular network controlled D2D communication to reduce error probability and signaling overhead. [30] introduces a multicast D2D model, and use it to analyze multicast metrics like the coverage probability, mean number of covered receivers and throughput. [31] provides a secure data sharing protocol, which merges the advantages of public key cryptography and symmetric encryption, to achieve data security in D2D communication. [32] proposes a social-aware approach for optimizing D2D communication by exploiting social network layer and physical wireless network layer. The physical layer D2D network is captured via the users' encounter histories. Given the social relations collected by the base station, an algorithm for optimizing the traffic offloading process in D2D communication is developed. However, these existing solutions either depend on frequent intervention of the base-stations or consider different networking and application settings in mobile opportunistic D2D networks, and thus not readily applicable in this work. To utilize the full potentiality of D2D network's paradigm, researches on effective data dissemination using minimal or no B2D communication have thus become an emerging field to study.

III. Problem Formulation

In this section, we formally formulate the problem of delay-constrained multi-copy multi-path least-cost multicasting in mobile opportunistic D2D networks.

Assume there are N nodes in the network and they form k opportunistic links. The delay of each link is a random variable denoted by T_l, $\forall 1 \leq l \leq k$. To formulate the delay-aware multicast problem, we define a $1 \times k$ binary transmission vector, Ω, for a data delivered from a source s to a given set of destinations Φ. Each element of the vector is a 0-1 variable to be optimized. If $\Omega_l = 1$, the link l is employed for data dissemination; otherwise, the communication opportunity will not be utilized. A transmission strategy, i.e., Ω, induces a total communication cost (defined as C_Ω), a path set (denoted as $\Psi_d, \forall d \in \Phi$) in which each path is the one from source to d, and a random variable (denoted as $\tau_d^i, \forall d \in \Phi, 1 \leq i \leq |\Psi_d|$) that represents the delay to deliver the data to d through the ith path in Ψ_d. Note that, due to nondeterministic connectivity, it is intrinsically impossible to provide a hard guarantee of end-to-end delivery delay. Thus, we adopt a probability-based delay budget in this work to achieve a desired probability to deliver data within a predefined delay budget.

Therefore the optimization problem is formulated as follows:

$$\begin{aligned} Minimize: \quad & C_\Omega, \\ S.t.: \quad & 1 - \textstyle\prod_{i=1}^{|\Psi_d|} (1 - Pr\{\tau_d^i \leq \delta\}) \geq \gamma, \forall d \in \Phi, \end{aligned} \tag{1}$$

aiming to minimize overall communication cost and at the same time reach a desired probability γ to deliver data to each destination through at lease one path within delay budget δ.

IV. Centralized Heuristic Algorithm

While the problem formulated above appears simple, it is nontrivial to be solved, since the nondeterministic network setting dramatically increases the complexity to derive Ψ_d and $Pr\{\tau_d^i \leq \delta\}$, resulting in the NP-hardness of the problem. More specifically, compared with single-copy single-path transmission, multi-copy multi-path transmission introduces new challenges. Since multiple copies are transmitted via different paths to each destination and such paths to each destination may overlap, it becomes extremely difficult to derive the end-to-end delays under the dependent transmissions of redundant copies.

In order to overcome the challenges introduced above, we design an efficient and scalable heuristic solution to convert the correlated copies into independent transmissions, in order to estimate the end-to-end delays. More specifically, we introduce a centralized heuristic algorithm which aims to discover a graph for multicasting (denoted by $\mathbb{G}$), in order to meet the constraint in Eq. (1) and achieves low communication cost. $\mathbb{G}$ can be considered as an approximation of the optimal Ω yielded from problem formulation.

Initially, the graph $\mathbb{G}$ includes the source node only and all destinations are put into the set Φ. The algorithm runs in iterations. Each iteration includes the following steps.

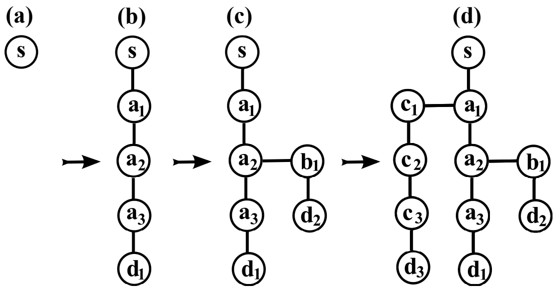


Fig. 1: An example of the centralized heuristic algorithm.

- First, it computes the paths from every destination in Φ to the current graph, which satisfy the constraint in Eq. (1) and at the same time introduce the least additional cost (e.g., the fewest links in addition to the current graph). How to efficiently determine these paths is to be discussed below.
- Second, the above step essentially creates $|\Phi|$ hypothetical new graphs, each augmenting the current graph by multiple paths. A metric, named extensibility, is computed to describe the goodness of each hypothetical graph. The destination that results in the smallest extensibility is chosen. It is removed from Φ, and the corresponding hypothetical graph replaces the current graph.
- The above steps repeat until Φ is empty.

Fig. 1 shows an example of augmenting the graph under the algorithm, until it covers all destinations. The algorithmic details are elaborated below.

A. Delay-Constrained Least-Cost Multi-Path Construction

Our delay-constrained least-cost multi-path construction is based on a state diagram. Each state is a vector with N elements, i.e., $S = [s_1, s_2, ..., s_N]$, where $s_i = -1$ signifies Node i has not received the data packet, $s_i = 0$ indicates Node i is carrying the data packet but has never transmitted it to another node, and $s_i = 1$ means Node i has received the data packet and forwarded it.

Fig. 2 illustrates an example of the state diagram for a network with four nodes. Without loss of generality, we let Node 1 be the data issuer. Thus the initial state is $S = [0, -1, -1, ..., -1]$. The state transits, as depicted by an arrow in the diagram, when the data packet is transmitted from one node to another, e.g., from Node i to Node j. Such a state transition is denoted by L_{ij}. Note that, different from single-copy single-path data transmission where L_{ij} is possible only if $s_i = 0$ and $s_j = -1$, i.e., Node i is carrying the data packet but has never transmitted it while Node j has not received the data packet, in multi-copy multi-path data transmission, data packet may be delivered to Node j even Node j has already received it.

The state diagram (including the states and transitions) forms a tree structure. The initial state is the root of the tree.

A state can be in two status, i.e., *active* or *terminated*, as defined below.

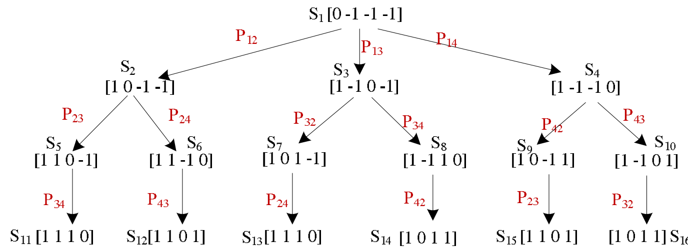


Fig. 2: The state diagram shows all possible transmissions of a data packet in a network with four nodes. Without loss of generality, we let Node 1 be the data issuer.

Definition 1. *An* active state *is a state that allows further transitions.*

The data packet will be further transmitted under an active state. An active state must have a 0 element, i.e., $s_i = 0$, which is also called an active element.

Definition 2. *Node i is an* active element *of an active state if and only if $s_i = 0$.*

Fig. 2 depicts active states only. Each active state may remain active or be terminated.

Definition 3. *An active state becomes a* terminated state *if the data packet is delivered to the destination.*

Fig. 2 depicts all possible transmissions of a data in a network. Our goal is not to execute all such transmissions which lead to high communication overhead, but instead to perform selective transmissions to minimize communication cost. To this end, we have introduced a transmission matrix, X, where $X_{ij} = 1$ signifies that Node i will send the data packet to Node j, when the former meets the latter with $s_i = 0$ and $s_j = -1$ or 1; or the transmission will not be performed otherwise.

With X as the variable to be optimized, we now analyze the probability to reach each state. Since the state diagram forms a tree structure, there is a unique path from the root (i.e., the initial state) to a given state $S = [s_1, s_2, ..., s_N]$. Let L_S denote the path from the root to S, which consists of a sequence of transmissions $\{L_{U_1^S U_2^S}, L_{U_2^S U_3^S}, ..., L_{U_{K-1}^S U_K^S}\}$, where $\{U_1^S, U_2^S, ..., U_K^S\}$ are the set of nodes involved in the transmissions in sequence. For example, the path from the root to State $S_{14}[1, 0, 1, 1]$ includes such links as L_{13}, L_{34}, and L_{42}. Each link introduces a transmission delay. The total delay to reach the state is $\sum_{i=1}^{K-1} T_{U_i^S U_{i+1}^S}$. In single-copy single-path data transmission, since only one path to each destination is selected, once the distribution of any individual opportunistic link delay (i.e., $T_{U_i^S U_{i+1}^S}$) is known, the distribution of a path delay can be derived by convolution. Thus once the path to d is determined, $Pr\{L_S \leq \delta\}$ can be calculated accordingly. However, in multi-copy multi-path data transmission, it is difficult to derive the probability to reach each state, because one link may be shared by different state transitions. In order to eliminate the dependence of multiple paths to the same destination, we apply edge splitting process [22] to derive independent delivery probability.

We are interested in terminated states. A state S can be terminated if and only if the following two conditions are satisfied. First, the transmission matrix is configured such that $X_{U_i^S U_{i+1}^S} = 1, \forall 1 \leq i \leq K-1$, forming a valid path from the root to State S. Second, the last node on the path (i.e., Node U_K^S) is the destination while others along the path (i.e., Nodes U_i^S, $\forall 1 \leq i \leq K-1$) are not. Therefore the probability that State S is terminated is

$$P_S(X) = \prod_{i=1}^{K-1} X_{U_i^S U_{i+1}^S} \times Pr\{\sum_{i=1}^{K-1} T_{U_i^S U_{i+1}^S} \leq \delta\}. \quad (2)$$

After the conversion from the dependent links to the indepent ones, the states are uncorrelated, therefore the total probability to reach a terminated state, i.e., the probability to deliver the data packet to the destination through at least one path is $P(X) = 1 - \prod_{|\Psi_S|}(1 - P_S(X))$, where $|\Psi_S|$ is the set of paths from the root to State S. With proper manipulation, we arrive at the following formula:

$$P(X) = 1 - \prod_{|\Psi_S|}(1 - \prod_{i=1}^{K-1} X_{U_i^S U_{i+1}^S} \times Pr\{\sum_{i=1}^{K-1} T_{U_i^S U_{i+1}^S} \leq \delta\}). \quad (3)$$

The communication cost in a wireless network is often proportional to the number of transmissions. The more the transmissions, the higher the consumption of energy and storage space. It is out the scope of this work to define the best cost function. We simply let $C(X)$ be the total number of transmissions involved in the delivery of a data packet. Let $D(S)$ denote the depth of State S in the diagram. Obviously, $D(S)$ represents the number of transmissions (i.e., the cost) needed to transit from the initial state to S. Note that, the cost of $D(S)$ is incurred as long as State S is reached. Thus $C(X)$ is given below:

$$C(X) = \sum_S D(S) P_S(X). \quad (4)$$

Thus, Eq. (1) can be reformulated as:

$$\begin{aligned} Minimize: &\quad C(X), \\ S.t.: &\quad P(X) \geq \gamma. \end{aligned} \quad (5)$$

$P(X)$ and $C(X)$ are obtained via Eqs. (3) and (4), and then plugged into Eq. (5). A branch and bound algorithm [33] is adopted here to discover the optimal transmission matrix X, in order to minimize $C(X)$ while ensuring $P(X) \geq \gamma$.

B. Best Hypothetical Graph Based on Extensibility

The above step establishes the delay-constrained least-cost multi-path to each node in Φ. If the paths do not exist for a destination, it is marked unreachable. It essentially creates up to $|\Phi|$ hypothetical new graphs, denoted by $\{\mathbb{G}_d | \forall d \in \Phi\}$. Next we introduce a metric, named extensibility, to choose the best hypothetical graph added to the current graph $\mathbb{G}$.

Each node d in Φ induces a hypothetical graph. Its extensibility is defined as

$$EX_d = \frac{1}{|\Phi| - 1} \sum_{i \in \Phi, i \neq d} C^i_{\mathbb{G}_d}, \quad (6)$$

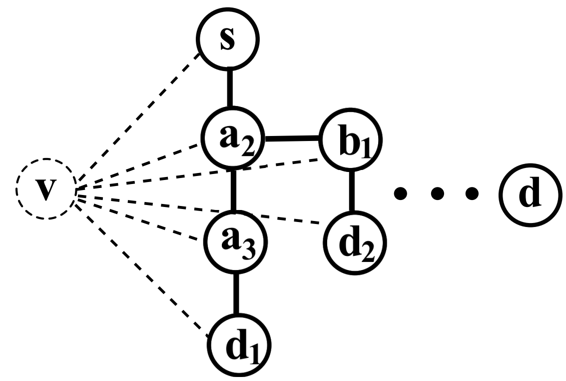


Fig. 3: To discover the delay-constrained least-cost path from a node in Φ to the current graph $\mathbb{G}$, a virtual node v is created and connected to every node in $\mathbb{G}$ via a virtual edge with a cost of zero.

which is intrinsically the average least cost from the remaining destinations to the hypothetical graph $\mathbb{G}_d$.

To solve the above least cost problem between a node and a graph, we create a virtual node v and connect it to every node in $\mathbb{G}$ via a virtual edge (as shown in Fig. 3). Each virtual edge has a cost of zero. Thus the least cost between v and a node d in Φ is equivalent to the least cost path from d to the multicast graph $\mathbb{G}$, where we can apply a shortest path algorithm to solve the problem.

The hypothetical graph with the lowest extensibility is selected, since it minimizes the average cost for future destinations to join the graph. Accordingly, $\mathbb{G}$ is replaced by $\mathbb{G}_d$ with minimum EX_d, and the corresponding d is removed from Φ.

The algorithm repeats the above process until all destinations have been added into the graph, i.e., $\Phi = \emptyset$.

V. Distributed Online Algorithm

While the above algorithm can be implemented by each individual node, it is intrinsically centralized (requiring global information), and thus unpractical for real world implementation. However, it offers useful insights for the development of a distributed data transmission strategy. In particular, the essence of the centralized algorithm is to determine multiple end-to-end paths from source to each destination by striking the balance between cost and delivery probability. This insight stimulates us to develop a distributed scheme to establish "virtual paths" from source to each destination which can significantly reduce the computation complexity and also effectively guide the transmission of a data packet to each destination with a required delivery probability.

The proposed algorithm consists of two components, which respectively establish an approximate multicast transmission strategy based on "virtual path" for each destination and make appropriate online routing decisions based on optimal stopping rule as outlined below.

A. Approximate Multicast Transmission Strategy

We propose to establish an approximate multicast transmission strategy to guide the transmission of a data packet to the destination with low computation complexity. Briefly, each node discovers a set of opportunistic links with its direct neighbors and maintains the corresponding delay distributions in order to construct an approximate network graph, including its direct neighbors and virtual paths which denote multi-hop paths from the neighbors to the destination. Compared with the centralized approach, where each node maintains the complete paths to each destination, in the distributed approach the source node only maintains the delay distributions and costs of virtual paths. In our implementation, we adopt discrete time slots to construct approximate delay distributions, where a slot is Δ minutes. The delay distribution of a direct link between Nodes i and j can be represented by a vector $[P_{ij}^1, P_{ij}^2, ..., P_{ij}^K]$, where P_{ij}^k is the probability that their inter-meeting time is greater than $(k-1)\Delta$ and less than $k\Delta$. Such an approximate delay distribution can be built via a trivial online learning algorithm according to historical inter-meeting times. The nodes exchange such information when they meet, to learn the remote opportunistic links up to a certain number of hops. Without loss of generality, let's consider a destination d. When Node i meets Node j, it intends to learn a set of available paths from Node j to d. More specifically, it builds a network graph which includes the direct link between Node i and Node j, the direct links from Nodes i and j to d, and virtual paths that represent multi-hop paths from Nodes i and j to d. Let L_{ij}^k denote a link between Node i and Node j, where k is an index. L_{ij}^0 indicates the direct link, and $L_{ij}^k (k > 0)$ represents the kth virtual link. L_{ij}^k is associated with a cost C_{ij}^k and a delay T_{ij}^k. The overall delay of path $i \to j \to d$ is $T_{ij}^0 + T_{jd}^k$. Its delay distribution can be calculated as the convolution of $[P_{ij}^1, P_{ij}^2, ..., P_{ij}^K]$ and $[P_{jd}^1, P_{jd}^2, ..., P_{jd}^K]$. The overall cost of path $i \to j \to d$ is $1 + C_{jd}^k$.

So far, the source has maintained multiple paths via each of different next hop relay nodes. We assume that the source delivers a data packet to destination $d, \forall d \in \Phi$, and selects paths via next hop relay node i among path set $P_d^i, \forall d \in \Phi$. The path selection is then formulated as follows:

$$\begin{aligned} Minimize: &\quad \sum_{i=1}^{m} \sum_{k=1}^{|P_d^i|} x_i^k c_i^k, \\ S.t.: &\quad 1 - \frac{1}{m} \sum_{i=1}^{m} \prod_{k=1}^{|P_d^i|} (1 - x_i^k p_i^k) \geq \gamma, \forall d \in \Phi, \end{aligned} \tag{7}$$

where x_i^k indicates whether or not the data packet is delivered by the kth path via the next hop relay node i. c_i^k denotes the cost of the kth path. p_i^k denotes the probability from the source through the kth path of the next hop relay node i to destination d. m is the number of next hop relay nodes. The constraint ensures that, the delivery probability that the data packet is delivered to each destination by at least one of the paths within a given delay budget is not less than γ.

The problem is NP-hard. We propose a heuristic approach. The weight for the next hop relay node i to deliver a data packets to all the destinations is

$$w_i = 1 - \frac{1}{|\Phi|} \sum_{d=1}^{|\Phi|} \sum_{k=1}^{|P_d^i|} \frac{x_i^k p_i^k}{|P_d^i|} \tag{8}$$

which indicates the probability that a data packet cannot be delivered to the destinations via the next hop relay node i within a given delay budget. Φ is the destination set. P_d^i is the set of paths via next hop relay node i to destination d. Then the next hop relay node is chosen by the following requirement:

$$\prod_{i=1}^{m} w_i^{x_i} \leq 1 - \gamma \tag{9}$$

where x_i indicates whether or not the data packet is delivered by the next relay node i. We apply 0-1 knapsack algorithm to determine the optimal next hop relay nodes. The source thus employs the heuristic algorithm to compute a transmission strategy based on the selected next hop relay nodes, in a distributed manner according to its best-known knowledge.

B. Online Dynamic Routing

The above algorithm can be implemented in a distributed manner according to its best-known knowledge of the network. However, such algorithm is essentially an offline solution. It intends to discover an optimal routing strategy based on the network graph, and transmits data according to the strategy. This approach is well accepted in conventional, deterministic networks. However, *it is inefficient in a mobile opportunistic network, since it intends to apply a deterministic transmission strategy in a nondeterministic network* by transmitting all data packets via a predetermined route. In mobile opportunistic D2D networks, the optimal routing strategy is the "best" only on a statistic basis when we consider a large number of data packets. It is not necessarily the best solution for every individual transmission.

For example, assume that under the optimal routing strategy, Node i should transmit data packets to Node j, which is the statistically optimal strategy. But when Node i intends to transmit a particular packet, it might not be able to establish a link with Node j within a delay budget. Therefore, the transmission would fail if it is determined to wait for Node j. Instead, it is obviously favorable to deliver the packet via other nodes it meets opportunistically. In general, Node i may meet a sequence of nodes, similar to a stochastic process. It must make an adaptive, online decision on which communication opportunity should be exploited to deliver the data packet, in order to achieve the optimization goal given in Eq. (1).

Based on the above observation, we propose a distributed online algorithm based on optimal stopping theory.

1) Analysis: Since we are concerned about the problem of delivering a data packet within a delay budget, we propose a distributed approach based on the stopping rule problem with finite horizon. A stopping rule problem has a finite horizon if there is a known upper bound on the number of stages at which one may stop.

We define V_ϵ the cost if the data packet is delivered by one node with remaining delay budget $(\delta-\epsilon)$. We note that $\{V_\epsilon\}$ are in fact a sequence of i.i.d. random variables. Thus we denote the probability density function (pdf) of V_ϵ as $f(v)$. We denote $Y_\epsilon = 1 - 1/V_\epsilon$ as the return node i can obtain if it deliveres a multicast data to one node at time ϵ. More specifically, $Y_\epsilon = V_\epsilon \cdot g_\epsilon$, where g_ϵ is the discounted factor capturing the essential idea that further delivery is at the cost of the decrease in the delay budget. We assume $Y_\delta = 0$ and $Y_\infty = 0$, which means that node i wins nothing if it waits until the delay budget expires or forever.

For the delay-constrained least-cost multicasting problem, node i will obtain Y_ϵ if it deliveres a multicast data to one node at time ϵ. Node i may decide to stop at time ϵ or to continue to meet other nodes. Therefore, the delay-constrained least-cost multicasting problem can be considered as an optimal stopping problem with an objective to find the optimal stopping time that maximizes the expected return, i.e.

$$\epsilon^* \triangleq \arg\max_{\epsilon}[E(Y_\epsilon)], Y^* \triangleq \sup_{\tau}[E(Y_\epsilon)]. \tag{10}$$

We define Z_ϵ as the maximum return node i can obtain if it delivers a data packet at time ϵ. At ϵ, we compare the return for stopping, namely Y_ϵ, with the return we expect to be able to get by continuing and using the optimal rule for time slots $\epsilon+1$ through δ, which at time slot ϵ is $E(Z_{\epsilon+1}(Y_{\epsilon+1}))$, i.e.

$$Z_\epsilon = \max\{Y_\epsilon, E(Z_{\epsilon+1}(Y_{\epsilon+1}))\} \tag{11}$$

From Eq. (11), we can see that $E(Z_{\epsilon+1}(Y_{\epsilon+1}))$ serves as a threshold in the sense that if Y_ϵ is above the threshold, it is optimal for the node to deliver the data packet. We define the threshold at time slot ϵ as

$$\rho^*_\epsilon = E(Z_{\epsilon+1}(Y_{\epsilon+1})), \tag{12}$$

Then we can obtain the optimal stopping strategy of the delay-constrained least-cost multicasting problem as follows.

Theorem 1. *For the delay-constrained least-cost multicasting problem, it is optimal for the node to deliver the data packet if the following condition is satisfied at* ϵ*,*

$$\epsilon^* = \inf_{\epsilon}\{\epsilon > 0 : Y_\epsilon \geq \rho_\epsilon\} \tag{13}$$

Theorem 2. *For the delay-constrained least-cost multicasting problem, the threshold of the optimal stopping strategy is given by:*

$$\rho^*_\delta = 0 \tag{14}$$

$$\rho^*_{\delta-1} = g_T \int_{V_d}^{V_{max}} v f(v) dv \tag{15}$$

$$\vdots$$

$$\rho^*_{\epsilon^*} = g_{\epsilon+1} \int_{\frac{\rho^*_{\epsilon+1}}{g_{\epsilon+1}}}^{V_{max}} v f(v) dv + \rho^*_{\epsilon+1} \int_{V_d}^{\frac{\rho^*_{\epsilon+1}}{g_{\epsilon+1}}} f(v) dv \tag{16}$$

Proof. We know that $Y_\delta = 0$, then according to Eq. (12), we get $\rho^*_\delta = 0$. Then we have $Y_\delta \geq \rho^*_\delta$. According to Eq. (12), we can obtain ρ^*_{T-1} as

$$\begin{aligned} \rho^*_{\delta-1} = &\ E[Z_\delta] = E[Y_\delta], \\ = &\ g_\delta E[V_\delta] = g_\delta \textstyle\int_{V_d}^{V_{max}} v f(v) dv \end{aligned} \tag{17}$$

Combining Eqs. (14) and (15), we can next compute $\{\rho^*_\epsilon\}_{\epsilon=0}^{\delta-2}$ by the backward induction as

$$\begin{aligned} &\rho^*_\epsilon = E[\max\{Y_\epsilon, \rho^*_{\epsilon+1}\}] = E[\max\{g_\epsilon V_\epsilon, \rho^*_{\epsilon+1}\}] = \\ &g_{\epsilon+1} \int_{\frac{\rho^*_{\epsilon+1}}{g_{\epsilon+1}}}^{V_{max}} v f(v) dv + \rho^*_{\epsilon+1} \int_{V_d}^{\frac{\rho^*_{\epsilon+1}}{g_{\epsilon+1}}} f(v) dv \end{aligned} \tag{18}$$

□

2) Protocol Design: To facilitate our discussion, we assume that each multicast data packet is associated with a descriptive metadata, which includes a source (i.e. s), a set of multicast destinations (i.e. Φ) and a sequence number (i.e. m).

After the packet is created by the source, it will be transmitted to a set of intermediate nodes based on the routing scheme to be introduced below. Each node carries a responsibility to deliver the packet to a subset of destinations. For example, let's assume Node i currently holds a multicast packet. It is responsible to deliver the packet to a set of destinations, $\Phi_i \subseteq \Phi$. Initially, $\Phi_i = \Phi$ if Node i is the source, and $\Phi_i = \emptyset$ for all other nodes. Let $\mathbb{G}_i(\Phi_i)$ denote the approximate multicast graph at Node i that intends to cover the destinations in Φ_i. It is composed by the paths of the selected next hop relay nodes according to the algorithm discussed in Sec. V-A. The cost of the graph is denoted by $C_{\mathbb{G}_i(\Phi_i),\tau}$, which is the sum of costs of all the paths via the selected next hop relay nodes, where τ is the current time slot.

We assume only two nodes meet at one time slot, if multiple nodes meet at one time slot, we assume an underlying medium access control protocol (e.g., IEEE 802.11) that randomly selects one node as the sender and another as the receiver. We consider Node i meets Node j at time slot τ, if the data packet is not delivered to Node j, then at the next time slot $\tau+1$, the cost of Node i to deliver the data packet will become $C_{\mathbb{G}_i(\Phi_i),\tau+1}$. On the other hand, if the data packet is delivered to Node j in time slot τ, two copies of the data packet are generated, each of which takes partial responsibility to deliver the data packet to the whole or partial destinations. When Node i meets Node j at time slot τ, the former instructs the latter to compute a multicast graph, aiming to cover the destination set Φ_i. Node j may or may not be able to cover the entire Φ_i. Let $\mathbb{G}_j(\Phi_j)$ denote the approximate graph constructed by Node j, where $\Phi_j \subseteq \Phi_i$. The cost of the two approximate graphs at time slot τ is $C_{\mathbb{G}_i(\Phi_i),\tau}$ and $C_{\mathbb{G}_j(\Phi_j),\tau}$ respectively.

According to Theorem 1, Node i transmits the packet to Node j, if and only if the following condition is satisfied:

$$\frac{1}{C_{\mathbb{G}_i(\Phi_i),\tau} + C_{\mathbb{G}_j(\Phi_j),\tau}} \geq \frac{1}{C_{\mathbb{G}_i(\Phi_i),\tau+1}}. \tag{19}$$

The above condition indicates that the cost can be reduced by splitting the delivery responsibilities between Nodes i and j.

If Node i does transmit the packet to Node j, it updates its destination set to be

$$\Phi_i \triangleq \Phi_i - \Phi_j. \tag{20}$$

Node i stops transmitting the multicast packet when either $\Phi_i = \emptyset$ or the delay budget expires.

VI. Simulation Results

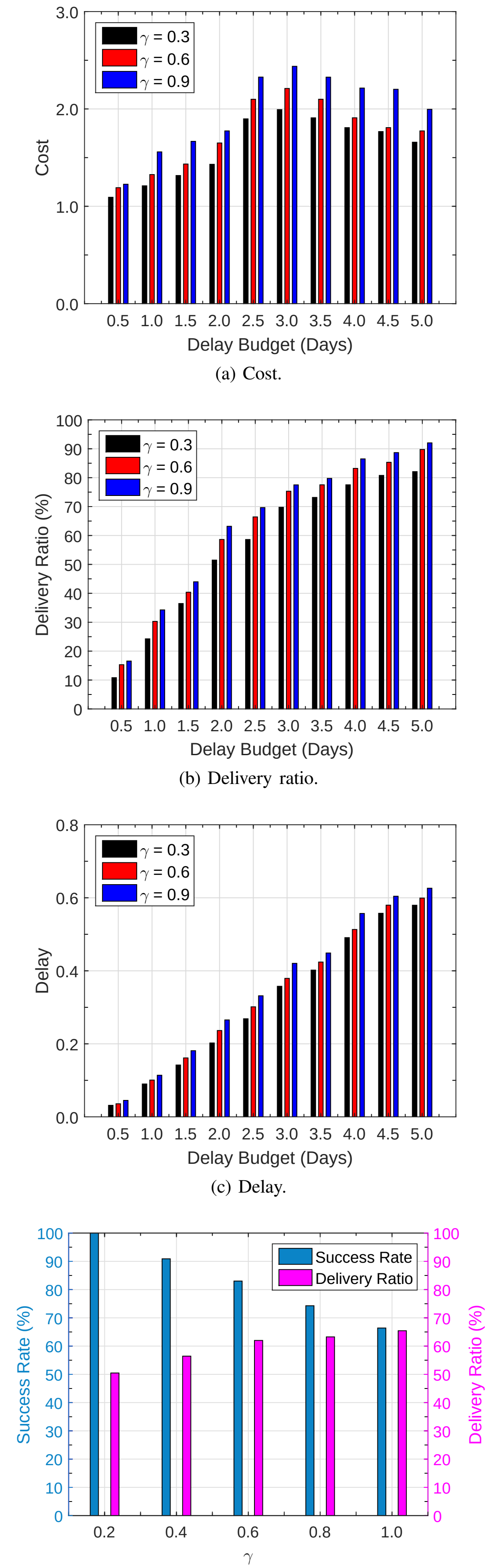
We have carried out extensive simulations to evaluate the proposed algorithms under various network settings. The simulation codes are extracted from our prototype implementation, and the simulation results are obtained under real-world traces and random walk mobility model. Each simulation is repeated 100 times with a random source node and a fixed number of randomly selected destinations for statistical convergence. We set the desired delivery probability 0.8.

A. Simulation under DieselNet Trace

We have evaluated our proposed schemes under several real-world traces. DieselNet testbed comprises 33 buses, serving an area of approximately 150 square miles. Our simulation is based on the trace data obtained in 2008 [34]. The results under other traces show similiar trend, thus are not shown due to space limit. Fig. 4 shows the simulation results of different schemes. We can see that Epidemic outperformes others. On the other hand, Direct Delivery performs the worst, since data packet is delivered only when two nodes meet. The proposed distributed algorithm performs better than Centralized and Social-Aware [22].

The performance of the proposed distributed online algorithm under different delay budgets is shown in Fig. 5. With the increase of delay budget, the average cost increases accordingly. This is because increasing delay budget results in more aggressively attempted transmissions, including longer paths, thus leading to higher average cost. At the same time, the delivery ratio and delay naturally increase with larger delay budget. However, when the delay budget is sufficiently large, the overall cost decreases. It is because there are more options of data delivery paths. As a result, the algorithm is able to choose the ones with lower cost. In addition, higher probability threshold γ generally results in higher cost, delay and average delivery ratio, because it enforces the nodes to adopt more aggressive approaches for data delivery. However, we would like to point out that the success rate (i.e., the fraction of multicast jobs that meet the delay requirements) decreases when γ increases as shown in Fig. 5d. This is because it becomes more difficult to achieve the constraint in Eq. (1), when γ is large.

Fig. 6 illustrates the results when we vary the size of destination set. In general, it is more challenging to achieve a delay-constrained multicasting for a larger destination set, thus leading to higher cost and longer delay. At the same time, the average delivery ratio and success rate both decrease.



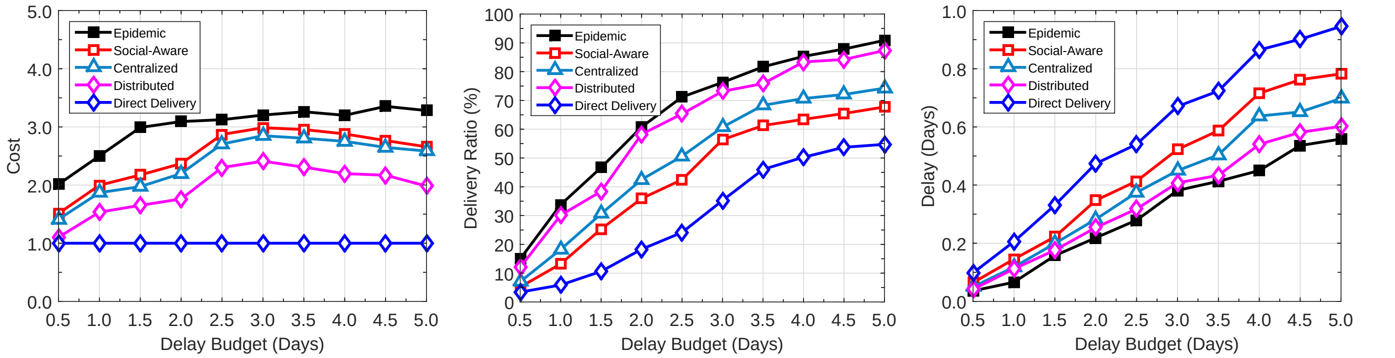
(a) Cost.

(b) Delivery ratio.

(c) Delay.

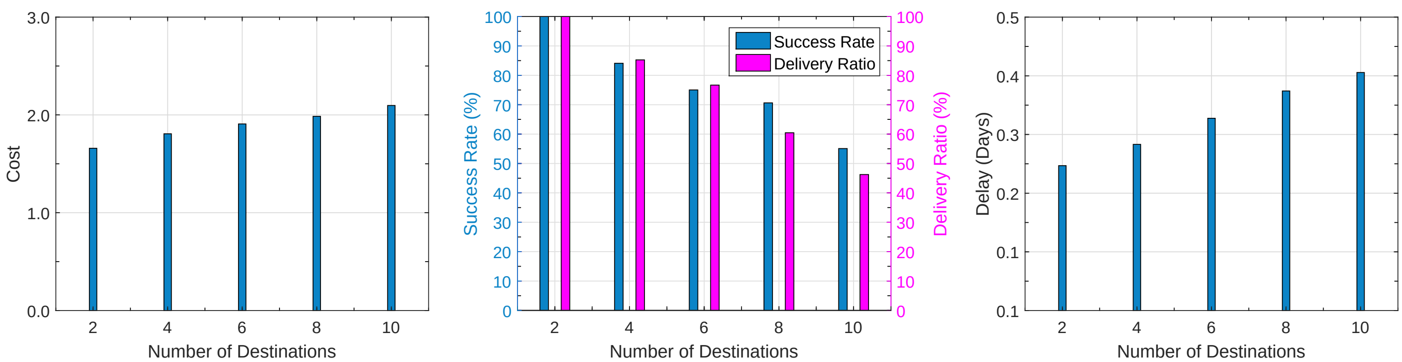
(d) Success rate vs. delivery ratio.

Fig. 5: Simulation results with different delay constraints under DieselNet trace.



(a) Cost. (b) Delivery ratio. (c) Delay.

Fig. 4: Performance comparison under DieselNet trace.



(a) Cost. (b) Success rate vs. delivery ratio. (c) Delay.

Fig. 6: Simulation results under different sizes of destination set under DieselNet trace.

B. Simulation under Random Walk Mobility Model

We have also carried out extensive simulations under random walk mobility model, which enables convenient study of performance trend with the variation of several network parameters. More specifically, the network is deployed in an area of 20×20. The network consists of 100 nodes and the generation rate of data packet is 0.02 (one packet per 50 time units).

As illustrated in Fig. 7a, with the increase of number of nodes in the network, the delivery ratio grows, because the nodes have more opportunities to meet each other and deliver their packets. The impact of traffic load is shown in Fig. 7b. While the delivery ratio keeps stable at the beginning under all schemes, it starts to drop when the generation rate exceeds 0.03. In general, with a higher packet generation rate, the overall traffic load increases, resulting in more frequent data overflow and consequently lower delivery ratio. Fig. 7c shows that a higher delivery ratio is achieved with the increase of queue size, because more packets can be kept in the queue until they are delivered.

VII. Conclusions

In this paper we have studied the problem of multi-copy data dissemination with probabilistic delay constraint in mobile opportunistic D2D networks. We have formally formulated the problem and introduced a centralized heuristic algorithm which aims to discover a network graph for multicasting, in order to meet delay constraint and achieve low communication cost. We have developed a distributed online algorithm based on the optimal stopping strategy. Simulation results based on real-world traces and random walk mobility model have proved the effectiveness of our proposed schemes and have shown that the overall performance depends on a variety of network parameters.

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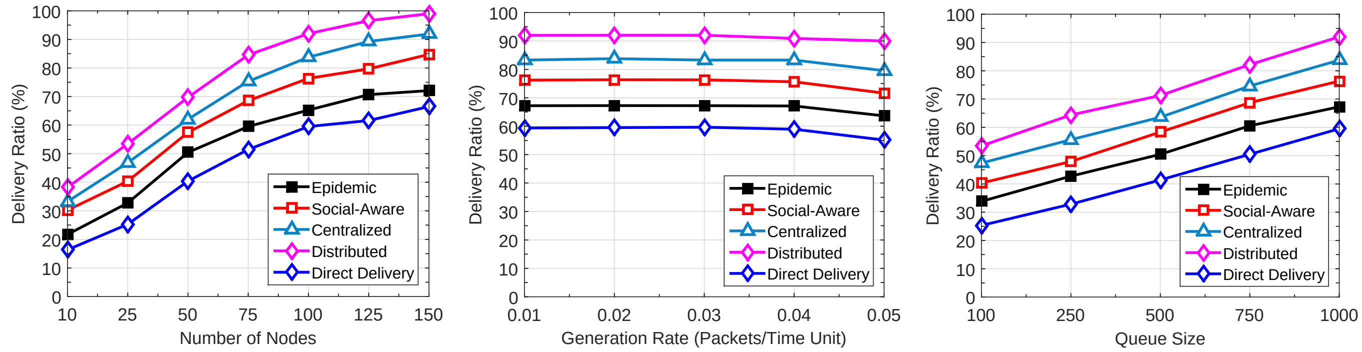

(a) Network density. (b) Traffic load. (c) Queue size.

Fig. 7: Performance comparison under random walk mobility model.

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