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Effective in Delay Tolerant Networks with More Destinations

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***Abstract*—We study the trade-off between delivery delay and energy consumption in a delay tolerant network in which a message (or a file) has to be delivered to each of several destinations by epidemic relaying. In addition to the destinations, there are several other nodes in the network that can assist in relaying the message. We first assume that, at every instant, all the nodes know the number of relays carrying the packet and the number of destinations that have received the packet. We formulate the problem as a controlled continuous time Markov chain and derive the optimal closed loop control (i.e., forwarding policy). However, in practice, the intermittent connectivity in the network implies that the nodes may not have the required perfect knowledge of the system state. To address this issue, we obtain an ODE (i.e., fluid) approximation for the optimally controlled Markov chain. This fluid approximation also yields an asymptotically optimal open loop policy. Finally, we evaluate the performance of the deterministic policy over finite networks. Numerical results show that this policy performs close to the optimal closed loop policy.**

I. INTRODUCTION

Delay tolerant networks (DTNs) [1] are sparse wireless ad hoc networks with highly mobile nodes. In these networks, the link between any two nodes is up when these are within each other's transmission range, and is down otherwise. In particular, at any given time, it is unlikely that there is a complete route between a source and its destination. We consider a DTN in which a short message (also referred to as a *packet*) needs to be delivered to multiple (say, M) destinations. There are also N potential relays that do not themselves "want" the message but can assist in relaying it to the nodes that do. At time t = 0, N_0 of the relays have copies of the packet. All nodes are assumed to be mobile. In such a network, a common technique to improve packet delivery delay is *epidemic* relaying [2]. We consider a controlled relaying scheme that works as follows. Whenever a node (relay or destination) carrying the packet meets a relay that does not have a copy of the packet, then the former has the option of either copying or not copying. When a node that has the packet meets a destination that does not, the packet can be delivered.

We want to minimize the duration to copy the packet to a significant (say α) fraction of the destinations receive the packet; we refer to this duration as *delivery delay*. On the one hand, copying the packet to a relay incurs a transmission cost. On the other hand, this copying increases the number of carriers of the packet and thereby potentially reduces the delivery delay. We focus on the problem of the control of forwarding.

II. RELATED WORK

Analysis and control of DTNs with single source and single-destination has been widely studied. Groenevelt et al. [3] modeled epidemic relaying and two-hop relaying using Markov chains, and derived the average delay and number of copies generated until the time of delivery.

Zhang et al. [4] developed a unified framework based on ordinary differential equations to study epidemic routing and its variants.

Neglia and Zhang [5] were the first to study the optimal control of relaying in DTNs with a single destination and multiple relays. They assumed that all the nodes have perfect knowledge of the number of nodes carrying the packet. Their optimal closed loop control is a threshold policy - when a relay that does not have a copy of the packet is met, the packet is copied if and only if the number of relays carrying the packet is below a threshold. Due to the assumption of complete knowledge, the performance reported is a lower bound for the cost in a real system.

Altman et al. [6] addressed the optimal relaying problem for a class of *monotone relay strategies* which includes epidemic relaying and two-hop relaying. In particular, they derived *static* and *dynamic* relaying policies.

Altman et al. [7] considered optimal discrete-time two-hop relaying. They also employed stochastic approximation to facilitate online estimation of network parameters.

In another paper, Altman et al. [8] considered a scenario where active nodes in the network continuously spend energy while *beaconing*. Their paper studied the joint problem of node activation and transmission power control.

Li et al. [9] considered several families of open loop controls and obtain optimal controls within each family. Deterministic fluid models expressed as ordinary differential equations have been used to approximate large Markovian systems.

Kurtz [10] obtained sufficient conditions for the convergence of Markov chains to such fluid limits.

Darling [11] considers the scenario when the Markovian system satisfies the conditions in [10] only
over a given set. He shows that the scaled processes, until they exit from this set, converge to a fluid limit. Darling and Norris [12] generalize the conditions for convergence, e.g., uniform convergence of the mean drifts of Markov chains and Lipschitz continuity of the limiting drift function, prescribed in [10]. Gast and Gaujal [13] use differential inclusions to address the scenario where the limiting drift functions are not continuous, and hence the differential equations are not well defined.

Gast et al. [14] study an optimization problem on a large Markovian system. They show that solving the limiting deterministic problem yields an asymptotically optimal policy for the original problem.

III. THE SYSTEM MODEL

We consider a set of K := M + N mobile nodes. These include M destinations and N relays. At t = 0, a packet is generated and immediately copied to N_0 relays (e.g., via a broadcast from a cellular network). Alternatively, these N_0 nodes can be thought of as source nodes.

1) Mobility Model: We model the point process of the *meeting instants* between pairs of nodes as independent Poisson point processes, each with rate λ. Groenevelt et al. [3] validate this model for a number of common mobility models (random walker, random direction, random waypoint). In particular, they establish its accuracy under the assumptions of small communication range and sufficiently high speed of nodes.

2) Communication Model: Two nodes may communicate only when they come within transmission range of each other, i.e., at the so called *meeting instants*. The transmissions are assumed to be instantaneous. We assume that that each transmission of the packet incurs unit energy expenditure at the transmitter.

3) Relaying Model: We assume that a controlled epidemic relay protocol is employed. Throughout, we use the terminology relating to the spread of infectious diseases. A node with a copy of the packet is said to be *infected*. A node is said to be *susceptible* until it receives a copy of the packet from another infected node. Thus at t = 0,N_0 nodes are infected while M + N − N_0 are susceptible.

A. THE FORWARDING PROBLEM

The packet has to be disseminated to all the M destinations. However, the goal is to minimize the duration until a fraction α (α < 1) of the destinations receive the packet. At each meeting epoch with a susceptible relay, an infected node (relay or destination) has to decide whether to copy the packet to the susceptible relay or not. Copying the packet incurs unit cost, but promotes the early delivery of the packet to the destinations. We wish to find the trade-off between these costs by minimizing

$$E\{T_d + \gamma E_c\} \quad (1)$$

where T_d is the time until which at least M_ := ⌈αM⌉ destinations receive the packet, E_c is the total energy consumption due to transmissions of the packet and γ is the parameter that relates energy consumption cost to delay cost. Varying γ helps studying the trade-off between the delay and the energy costs.

B. OPTIMAL FORWARDING

We derive the optimal forwarding policy under the assumption that, at any instant of time, all the nodes have full information about the number of relays carrying the packet and the number of destinations that have received the packet.

IV. ASYMPTOTICALLY OPTIMAL FORWARDING

In states [M_ − 1] × [N_0 : N] × {r}, the optimal action, which is governed by the function _(m, n), requires perfect knowledge of the network state (i.e., m and n). However this may not be available to the decision maker due to intermittent connectivity. In this section, we derive an asymptotically optimal policy that does not require knowledge of network's state but depends only on the time elapsed since the generation of the packet. Such a policy is implementable if the packet is time-stamped on generation and nodes' clocks are synchronized.

A. ASYMPTOTIC DETERMINISTIC DYNAMICS

Our analysis closely follows Darling [11]. It is straightforward to show that following are the conditional expected drift rates of the optimally controlled CTMC. For (m(t), n(t)) ∈ [M − 1] × [N_0 : N],dE(m(t)|(m(t),n(t))).

Markov Decision Process (MDP) Formulation

Let to and tk denote the meeting epochs of the infected nodes (relays or destinations) with the susceptible nodes. Define for $ and K>1. Let m(t) and n(t) be the numbers of infected destinations and relays, respectively.

B. ASYMPTOTICALLY OPTIMAL POLICY

Observe that φ(x, y) is decreasing in x and y both of which increase with t. Consequently φ(x(t), y(t)) decreases with t. We define $\tau_* := \inf\{t \geq 0 : \varphi(x(t), y(t)) \leq 0\}$. The limiting deterministic dynamics suggests the following policy u_∞ for the original forwarding problem.

V. OVERVIEW OFTHE PROPOSED MECHANISM

To recover the problem of existing system, we obtain an ODE approximation for the optimally controlled Markov chain. This fluid approximation also yields an asymptotically optimal open loop policy. Finally, we evaluate the performance of the deterministic policy over finite networks. We formulate the problem as a controlled continuous time Markov chain (CTMC), and obtain the optimal policy. The optimal policy relies on complete information of the network state, but availability of such information is constrained by the same connectivity problem that limits packet delivery.

VI. ALGORITHM

DSDV (Destination-Sequence Distance Vector)

DSDV has one routing table, each entry in the table contains: destination address, number of hops toward destination, next hop address. Routing table contains all the destinations that one node can communicate. When a source A communicates with a destination B, it looks up routing table for the entry which contains destination address as B. Next hop address C was taken from that entry. A then sends its packets to C and asks C to forward to B. C and other intermediate nodes will work in a similar way until the packets reach B.

DSDV use two types of packet to transfer routing information: full dump and incremental packet. The first time two DSDV nodes meet, they exchange all of their available routing information in full dump packet. From that time, they only use incremental packets to notice about change in the routing table to reduce the packet size. Every node in DSDV has to send update routing information periodically. If two routes have the same sequence number, route with smaller hop count to destination will be chosen. DSDV has advantages of simple routing table format, simple routing operation and guarantee loop-freedom. The disadvantages are (i) a large overhead caused by periodical update (ii) waste resource for finding all possible routes between each pair, but only one route is used.

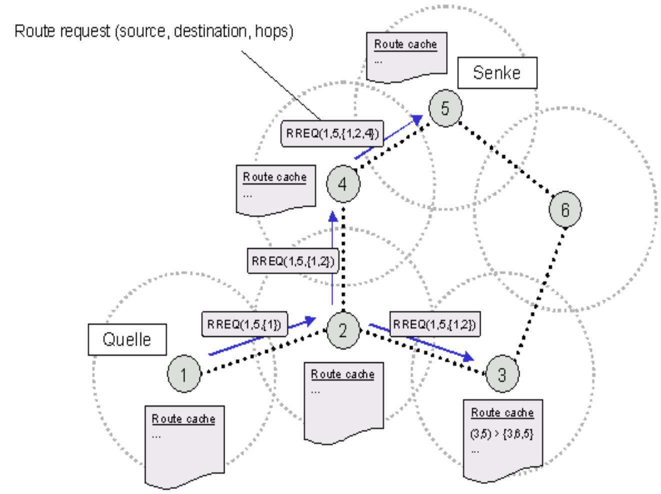

Figure 1: Path Finding Process: Route Request

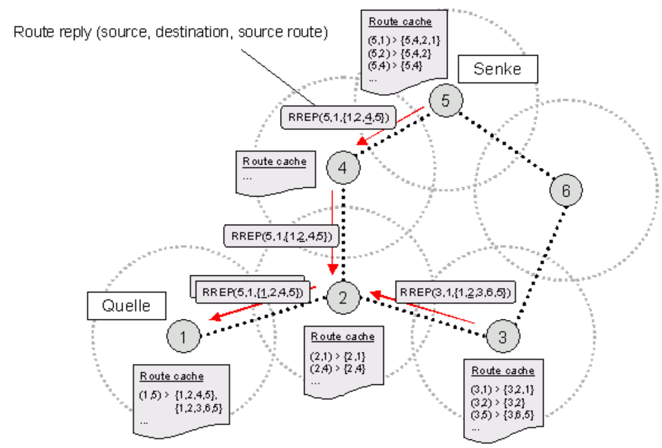

Figure 2: Path Finding Process: Route Reply

VII. PERFORMANCE EVALUATION

We now show some numerical results to demonstrate the performance of the deterministic control. Let X = 0.2, Y = 0.8, $\alpha = 0.8$, Y0 = 0.2 and $\gamma = 0.5$. We vary λ from 0.00005 to 0.05 and use K = 50, 100 and 200. we plot the total number of copies to relays and the delivery delays corresponding to both the optimal and the asymptotically optimal deterministic policies. Evidently, the deterministic policy performs close to the optimal policy on both the fronts. We observe that, for a fixed K, both the mean delivery delay and the mean number of copies to relays decrease as λ increases. We also observe that, for a fixed λ, the mean delivery delay decreases as the network size grows. Finally, for smaller values of λ, the mean number of copies to relays increases with the network size, and for larger values of λ, vice-versa happens.

A. Performance Metrics

We evaluate mainly the performance according to the following metrics.

False positive: In case of network failure, nodes may be falsely accused of misbehavior. The false positive should be kept low.

Detection Efficiency: The ratio of detected misbehaving nodes to the total number of nodes.

Delay Constraint: The delay constraint is averaged over all surviving data packets from the sources to the destinations.

B. Results

Node Creation on set the values from source to Multiple Destinations. Neighbour Discovery to find the all nodes and packet transfer from source to multiple destinations. Finally, find the best path from source to multiple destinations on Figure1. Then find the xgraph on Packet Delivery Ratio of Figure 2.

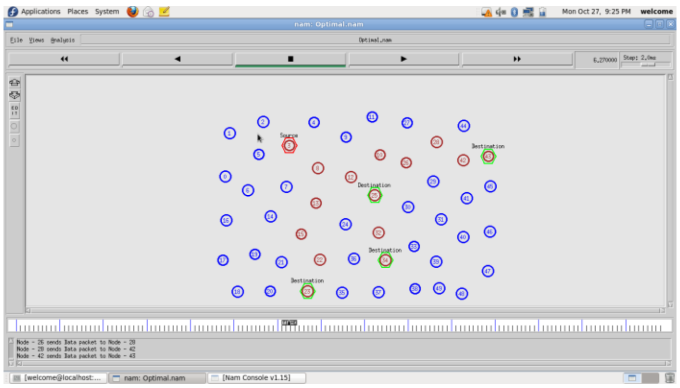

Figure 1: Find the Best Path from Source to Multiple Destinations.

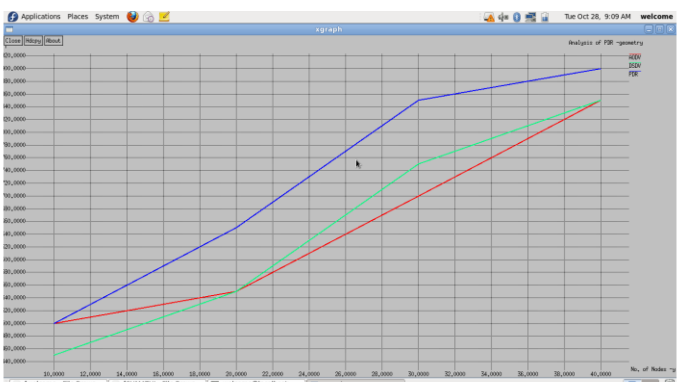

Figure2: show the results of xgraph on Packet Delivery Ratio.

VIII. CONCLUSION

In this research work, We have developed the control of forwarding in DTNs employing epidemic relaying, and obtained the optimal policy. We obtained an asymptotically optimal policy that does not require any information on the dynamic network state, and hence is feasible. In order to do so, we also extended the existing differential equation approximation results for Markov chains to controlled Markov chains. In our future work we want to study the scenario where packets come with a life-time and the goal is to maximize the fraction of destinations that receive the packet subject to the energy constraint. We also want to study the adaptive controls for the case when the network parameters (M,N, λ etc.) are not known to the source.

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