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Energy Sharing based Content Delivery in Mobile Social Networks

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***Abstract*—In mobile social networks, the mobility and connectivity of nodes are often non-deterministic. Source and destination nodes may not have a meeting opportunity and the content dissemination and delivery most of the time require the cooperation of nodes. However, this causes nodes spend energy, thus, they may be reluctant to participate in the dissemination process to conserve energy. One approach to motivate user participation is to transfer energy for their service so that their potential loss is compensated. However, this makes routing problem much challenging as the source node needs to decide not only the best relay nodes but also the amount of energy transfer to them. In this paper, we study this energy sharing based content delivery problem in mobile social networks. To this end, we assume that a node is willing to carry the content as long as the energy received for this delivery lasts, after which it drops the content (i.e., time-to-live). We utilize optimal stopping theory and dynamic programming to model the content delivery problem under this energy sharing paradigm between the nodes. The simulation results show that energy sharing based content delivery can potentially increase the routing performance under certain settings.**

***Index Terms*—Mobile social networks, energy sharing, dynamic programming, optimal stopping theory.**

I. Introduction

The dynamic mobility and connectivity of the nodes in opportunistic networks makes the dissemination and the delivery of content very challenging. There have been numerous works [1]–[3] in the literature that look at this problem under different settings and propose different routing algorithms in such networks. While the main focus has been to decide on the selection of the relay nodes to optimize the routing performance (e.g., better delivery ratio), most of the time it is assumed that there is already an incentive to carry the others' messages. Some of the works have studied the incentive oriented routing through tit-for-tat style [4] or credit-based [5] solutions. Some others have also considered the problem under social-selfishness [6] of nodes (i.e., being selfish to strangers and unselfish to friends) and provided trust management based solutions. However, such solutions compensate the actual energy consumption of relay nodes indirectly.

In some recent interesting works [7]–[9], this problem has been studied through energy sharing to relay nodes, providing direct compensation for the energy loss of nodes. In other words, a node with a content to be delivered to a destination transfers not only the content (e.g., copy of the message) but also sufficient energy to relay nodes, as an incentive to them to carry this content to the destination. Note that such an energy sharing between nodes can be performed in a convenient way, thanks to the recent advances [10] in wireless power transfer[1] and related developments to integrate them to mobile devices [11]–[13]. In the previous work, however, the problem is studied in a limited scenario, in which only the source node with unlimited energy resources gives the content and the energy to relay nodes with the goal of minimum energy consumption for the delivery. In a more general scenario, source node may have a limited energy budget for the delivery. Moreover, both the source node and the relay nodes can distribute the content and energy to other relay nodes met. However, this makes the problem more challenging as a more comprehensive approach has to be followed to determine not only the distribution of the content to relay nodes but also the amount of energy to be given to each of them.

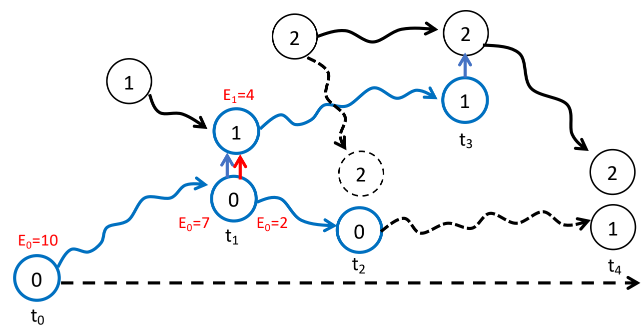

Fig. 1: An illustration of energy sharing based content delivery in opportunistic networks, where energy is used as an incentive to carry a message copy. Message carrying nodes and their tracks are shown in blue. Alternative path for node 2 and the path after node 0 stops carrying the message is shown with dotted lines.

A. Motivating Example

Consider the example in Fig. 1 with source node 0 having a message to deliver to destination node 2 and having an initial

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[1]While we do not restrict the proposed solution in this paper to only wireless power transfer based energy sharing, we also consider the impact of associated parameters (e.g., transfer efficiency) in the design of the proposed solution.

energy budget of 10 units to be used in the delivery of this message (i.e., node's actual energy may be more). Assume that each node consumes 1 unit of energy at every time unit while carrying the message. When node 0 meets node 1 at time t_1, it has a remaining energy budget of 7 units (as it spent 3 units of energy from t_0 to t_1). Node 0 predicts that its energy is more than enough to carry the message until it meets the destination with a high probability. Thus, to increase the delivery probability further, it decides to share 5 units of its energy with node 1 to have a better collaborative delivery probability than its individual delivery probability. Note that, due to the transfer efficiency, node 1 can only get 4 units of energy. After t_1, both nodes have a copy of the message and try to meet with the destination for delivery. Node 1 carries the message only 4 time units and node 0 carries the message only 2 times units after t_1. The message is delivered to node 2 at time t_3 by node 1. However, if node 2 were to follow an alternative predicted path, node 0 would deliver the message.

In a more general context, consider that node 0 and node 1 has met and node 0 has a message with some budget of energy. The options for node 0 are (i) to forward the content and available energy budget entirely (i.e., without keeping a copy and potentially with some loss during content/energy transfer), (ii) to keep the content and energy totally, or (iii) to give a copy of the content with some energy. The first two options are exactly similar to the decisions made in single-copy or forwarding based routing algorithms [14]. However, the third option is different than multi-copy based routing algorithms [15]–[19] as it divides the available energy to keep the content among nodes, thus essentially decreases time-to-live (TTL) of the messages or the deadline for delivery (on the contrary, in multi-copy based routing algorithms, the deadline is not changed). While multiple nodes carrying the content increase the likelihood for delivery, their smaller TTL values decrease the delivery chance. Such content and energy sharing can indeed provide a better cooperative delivery probability with a careful and thorough decision process. In particular, in mobile social networks where messages can get lost during opportunistic content transfers between nodes, the benefit gets more pronounced.

Consider the network graph in Fig. 2 which shows the mean intermeeting times of three nodes as the link weights. The lower chart shows the delivery probability of both node 0 and node 1 for destination 2 for different TTL values. Note that for node 0, this represents a *comprehensive* [15] delivery rate including both the direct delivery and delivery through node 1, while for node 1 it is the direct delivery rate. We also assume a link loss rate of 0.1 (i.e., a message is lost with 0.1 probability during transfer from a node to another), thus the expected delivery rates will only reach 90% at most. If node 0 meets node 1 and has a remaining TTL budget of 200 time units or less (which could be obtained by dividing energy budget available by energy consumption rate), the combined delivery rate (shown in red) suggests that it should forward both the content and energy entirely as node 1 offers better delivery rate. However, if it had TTL budget of 300 time units

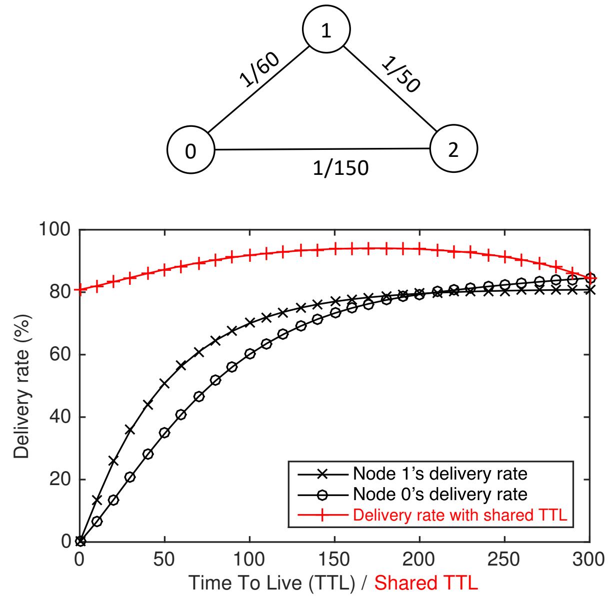

Fig. 2: An example opportunistic network with mean intermeeting times denoted as the weights of the edges on the graph. The source node is 0 and the destination node is 2. The lower graph shows both the individual delivery ratios of node 0 and node 1 and the cumulative delivery ratio when they share the total energy and TTL.

at the meeting time, the best strategy would be sharing of around half of the energy (or the corresponding TTL) with a copy of the content (assuming energy consumption rates of the nodes are similar and there is no loss during energy transfer).

B. Contributions

In this paper, we study the optimal content delivery problem through sharing of both the content and the energy among the nodes in a mobile social network. The content delivery in mobile social networks happens through opportunistic non-deterministic meetings of nodes and the design of most protocols usually depends on the analysis of historical contact information [20] with the expectation that the mobility of nodes shows long-term regularities (e.g., friendship [3]). That is, for example, if some pairs of nodes meet more frequently compared to other pairs, the same is in general expected consistently over time. In this paper, we consider a mobile social network where the long-term mean intermeeting times between nodes can be estimated from the contact history of the nodes. We assume each node has a complete information about the intermeeting times between all pairs of nodes in the network. However, in simulations, we relax this assumption and show the performance of the proposed algorithm with partial available information. Based on the available knowledge and the source's limited energy budget, our goal is to find the optimal policy for both content and energy sharing among nodes to achieve the best delivery rate. We utilize optimal stopping theory [21] and dynamic programming [22] to model and solve this problem under different settings (e.g., link loss rate, transfer efficiency rate). We also evaluate the performance of the proposed sharing based solution with simulations and show its benefit over just forwarding/keeping based strategy.

The rest of the paper is structured as follows. In Section II, we give a background on the literature utilizing energy sharing in mobile social networks and provide an overview of optimal stopping theory. In Section III, we provide the details of the proposed optimal decision process for content and energy sharing. Section IV provides the simulation settings and performance evaluation of the proposed approach. Finally, we provide the concluding remarks and outline the future work in Section V.

II. Background

A. Energy Sharing in Mobile Social Networks

The concept of (wireless) energy transfer to mobile nodes has a remarkable literature within the context of wireless sensor networks. It is assumed that there is a (multiple) mobile charging vehicle(s) (MCV) that charges the sensor nodes regularly in order to keep them alive and prolong the network lifetime [23]–[25]. Often the goal is to find the optimal visiting schedule of the MCV among the static sensor nodes such that it will keep them functional and will be back to the charging station without depleting its energy.

Recently, energy sharing has also been considered in different mobile network applications such as mobile social networks and vehicular networks [26]–[28]. The ability to exchange energy between nodes has made researchers rethink some of the existing solutions and benefit from the energy sharing concept for further optimization. There are also new challenging problems defined integrating the energy sharing concept. Such problems include finding optimal energy usage [29]–[33] and energy balancing [34]–[37] among the nodes in the network. In the former, the goal is to take the advantage of opportunistic interaction of nodes in a mobile social network to optimize the energy usage at nodes through sharing of energy between each other. That is, nodes with higher energy share some of their excessive energy with others in need of energy and receive back when they need. In the latter, however, the goal is to reach a certain target energy distribution among nodes as soon as possible from a given energy distribution at nodes through energy transfers in opportunistic meetings.

Energy sharing among nodes has also been considered [7]–[9] within the existing problem of content delivery in mobile social networks. Assuming that the relay nodes are only motivated by the energy they receive for the carrying of the content, the problem of content delivery is integrated with a joint energy sharing problem among nodes. A node with a message transfers not only the content but also some energy to relay nodes as an incentive to them to carry this content to the destination as long as the energy lasts. In [7], the problem is formulated using a Markov decision process (MDP) based on the contact state of content source to obtain the optimal energy sharing policy. The content source moves and visits a charger to receive energy and when it meets with a messenger (e.g., relay), asks for the delivery of the content to the destination node by sharing some energy to the messenger. If the energy depletes before reaching to the destination, the content is discarded by the messenger. MDP is used to carefully select a messenger node and transfer optimal energy so that the content is delivered to the destination with highest probability. Extending this study in [38] the authors show that the optimal strategy obtained by MDP is a threshold policy. In order to avoid the cumbersome of centralized solutions and achieve a decentralized decision policy, the problem is also formulated using a decentralized partially observable Markov decision process with constraints and a decentralized learning algorithm is proposed to obtain an optimal local policy at nodes [39]. The interaction between the source and the messenger nodes has also been modeled using game theoretical models in several studies. In [8] the peer-to-peer relations between mobile nodes are exploited to form a coalition to help one another on delivering a packet. They also look at the cases when these coalitions might not be beneficial and some nodes might decide to deviate away from coalition. The coalition in mobile nodes only aims to help in message delivery but not in replenishment of energy. A different approach based on forming a non-cooperative game model is considered in [9]. The source node, which is considered as a stable access point, holds an auction for wireless energy and the nodes send their bids for it. In return of service, the nodes have to pay certain cost to the source. A stochastic dynamic response algorithm is presented to adapt the strategies of nodes to the Nash Equilibrium which is proved to be the optimal policy.

Different than the focus of the aforementioned works, in this paper, we consider the problem of both content and energy sharing in mobile social networks in a general perspective. We assume all nodes are mobile and the content and energy sharing can happen between any pair of nodes as long as it helps for better delivery. To this end, we model the problem using optimal stopping theory [21] and dynamic programming [22] and show that it can improve the delivery ratio through simulations.

B. Optimal Stopping Theory

The theory of optimal stopping [21] deals with the problem of deciding the optimal time to take a given action based on a set of sequential observations to maximize an expected reward or to minimize an expected cost. These observations are usually assumed to be random variables with a known joint distribution. Well-known problems solved via optimal stopping theory include secretary hiring problem [40] and parking problem.

In an optimal stopping rule problem, you may observe a sequence X_1, X_2, ... for as long as you wish, where X_1, X_2, ... are random variables whose joint distribution is assumed to be known. For each stage t = 1, 2, ... after observing X_1, X_2, ... X_t, you may stop and receive the known reward y_t, or you may continue and observe X_{t+1}. The optimal stopping rule is to stop at some stage t to maximize the expected reward.

An optimal stopping rule problem has a finite horizon if there is a known upper bound on the number of stages at which one may stop. In other words, if there are only T observations possible before making a decision, the problem has a horizon of T. Such finite horizon optimal stopping problems can be solved by using *backward induction* method. That is, as the last stage to stop is T, optimal rule for the stage $T-1$ can be found first, then based on this optimal rule for stage $T-1$, optimal rule at stage $T-2$ can be found and so on. This process can be chained until the initial stage 0. As defined in [21], let $V_t^{(T)}$ ($1 \leq t \leq T$) represent the maximum expected reward one can obtain starting from stage t and let $V_t^T = y_T$ and then inductively for $t = T-1$, backward to $t = 0$,

$$V_t^{(T)} = \max\{y_t, E(V_{t+1}^{(T)})\}. \tag{1}$$

That is, we compare the reward (i.e., y_t) for stopping at stage t, with the expected reward $E(V_{t+1}^{(T)})$ to get by continuing to the next stage under the assumption that we will use the optimal rules for all stages from $t+1$ to T. If the $V_t^{(T)} = y_t$, that is $y_t \geq E(V_{t+1}^{(T)})$, it is better to stop at stage t. Otherwise, we continue making new observations.

III. System Model

A. Assumptions

Let $\mathcal{N}$=$\{0, 1, 2 \ldots n-1\}$ denote the set of $|\mathcal{N}| = n$ nodes in a mobile social network. Without loss of generality, we assume that 0 is the source node and $n-1$ is the destination node. The message at the source node has to be delivered to the destination node. We assume that source node has an initial energy budget, $\mathcal{E}$, to be used in the delivery of the message. Note that this energy budget can easily be converted to an estimated time-to-live (TTL) value for the message by dividing the energy by the energy consumption rate of the node, as it will be shown in next section. This also helps modeling the problem using optimal stopping theory with discrete time steps. A message is maintained until the TTL value lasts. When the source node is met with another node, it determines if it is useful to give a copy of the content and how much of its energy should be shared.

We assume that all nodes in the network have energy receiving and transferring capabilities (e.g., Samsung Galaxy S10, Huawei Mate 20 Pro) and energy sharing could be achieved via wireless energy transfer with a transfer efficiency of λ. The encountered node informs the source node or any other relay who has the content about how different its energy consumption than the source node's energy consumption rate, so that corresponding TTL at the encountered node with a specific amount of transferred energy could be found. The meetings of different pairs of nodes are assumed independent and the intermeeting times are exponentially distributed. However, the proposed algorithm can easily be updated under different distribution assumptions. We assume that the mobility of nodes exhibits long-term regularities, as it is assumed in related previous work [7], [15]. Thus, we initially assume that each node has the knowledge of mean intermeeting time information, $I_{i,j}$, for all pairs of nodes. We then relax this assumption and study the performance of the proposed solution when different levels of partial information is available to the nodes. We also assume that the links between nodes are lossy and the content will be dropped with some probability, denoted by γ, during transfers between nodes. This notion of link loss rates can be considered as a result of link failures or faulty relay nodes in the network which accept the incentive but deviates away from the delivery process. The notations used throughout the paper are summarized in Table I.

Notation	Description
n	Total number of nodes in the network.
$\mathcal{I}_{i,j}$	Mean intermeeting time of nodes i and j.
$\mathcal{M}_{i,j}$	Meeting probability of two nodes i and j at each time slot.
U	The size of each time slot.
$\mathcal{E}$	Initial energy budget to be used in the delivery of the content.
$\mathcal{E}_i$	Energy incentive held by node i to be used in the delivery of the content.
t_i	TTL of the content carried by node i.
t_i^+	TTL of the content carried by node i in the next time slot.
$\mathcal{E}_{i\to j}(t_i)$	The optimal energy that needs to be shared from node i to node j when it has a TTL of t_i.
e_i	Energy consumption rate of node i at each time slot.
$\mathcal{P}_{i,d,k,t}$	Probability that the content is delivered from source i to destination d with remaining TTL value of t in up to k hops.
K	The maximum number of hops that a content can be forwarded before it reaches destination.
γ	Link loss rate (i.e., content drop rate) between two nodes.
λ	Energy transfer efficiency rate.

TABLE I: Notations

B. Energy and Residual Time-to-Live relation

Let $\mathcal{E}_i$ denote the energy budget of the node i to be used in the delivery of the message, and e_i denote its average energy consumption rate. The discrete remaining time-to-live (TTL) value that it will keep the message using that energy, t_i, will be:

$$t_i = \mathcal{E}_i / e_i \tag{2}$$

When this node meets with another node j, it can either keep, forward or share the content/energy with j if it estimates that the likelihood of the message delivery will increase. Let $\mathcal{E}_{i\to j}(t_i)$ denote the optimal energy that needs to be shared from node i to node j when it has a TTL of t_i. The corresponding remaining TTL values of each node after this exchange (i.e., in the next time unit) will be:

$$t_i^+ = \frac{\mathcal{E}_i - \mathcal{E}_{i\to j}(t_i)}{e_i} - 1 \tag{3}$$

$$t_j^+ = \begin{cases} \frac{\lambda \mathcal{E}_{i\to j}(t_i)}{e_j}, & \text{if } r[0,1] \leq \gamma \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

Here, $r[0, 1]$ is a random number between 0 and 1. Note that the TTL value of node j should be estimated by taking into

TTL	Decision with forwarding	
t	$P_{i,d,k,t}$	
$t-1$	Not Forward $P_{i,d,k,t-1}$	Forward $P_{j,d,k-1,t-1} \times (1-\gamma)$
TTL	**Decision with sharing**	
t	$P_{i,d,k,t}$	
$t-1$	Not Share $P_{i,d,k,t-1}$	Share (1-γ) $\times$ [1-(1-P_{i,d,k_i^*,t_i^*})$\times$ (1-P_{j,d,k_j^*,t_j^*})] + (γ) $\times$ P_{i,d,k_i^*,t_i^*}

TABLE II: Decisions with forwarding and sharing.

account the energy consumption rate of node j as well as the energy transfer efficiency, λ. For node i, it also needs to consider the energy consumption at the current time (hence the -1 in (3)). If the content transfer is not successful due to the link loss rate, the TTL value of node j, will be assigned to 0, as having energy incentive for a message not received will be nonsense.

C. Optimal Content and Energy Sharing

We divide the time into equal size slots and assume that in each time slot, a node can either meet or not meet with another node. The intermeeting times of two nodes i and j are assumed to follow an exponential distribution with a mean of $\mathcal{I}_{i,j}$. Then, the meeting probability of two nodes i and j in each time slot of size U, denoted as $\mathcal{M}_{i,j}$, can be computed by

$$\mathcal{M}_{i,j} = 1 - e^{-U/\mathcal{I}_{i,j}}. \tag{5}$$

We adopt exponential distribution for intermeeting time distributions between nodes since it is a relatively general model [15]–[18], however, the proposed solution can be adapted to other distributions.

In our model, we follow a similar terminology introduced in [15] and adopt a hop count limited opportunistic forwarding protocol. That is, there is a hop count limit of K indicating the maximum number of hops a message can be forwarded before it reaches destination. Such a forwarding scheme also helps achieve scalability as it can limit the forwarding cost per message delivery which is usually assumed to be the major cost for routing in mobile social networks. When a message with a hop limit of k is forwarded to another node, its remaining hop count limit becomes $k-1$. When a node has a message with $k=0$, it can no longer forward the message to another node but still can deliver it to the destination.

Let $\mathcal{P}_{i,d,k,t}$ denote the delivery probability of a message at node i for destination d with a remaining hop count of k and a remaining time-to-live (TTL) value of t. The direct delivery probability of the message, with $k=0$, can be estimated by,

$$\mathcal{P}_{i,d,0,t} = \left(1 - e^{-tU/\mathcal{I}_{i,d}}\right) \times (1-\gamma) \tag{6}$$

The first part defines the meeting probability of node i with node d during t time slots and the second part considers the likelihood that the content will be lost during transfer, hence it will not be delivered.

Algorithm 1: $P_{i,d,k,t}$ calculation with optimal forwarding

```
1  P_{i,d,k,t} ← M_{i,d} × (1 − γ)
2  R_p ← 1 − M_{i,d}
3  for ∀j ∈ N s.t. j ≠ i and j ≠ d and M_{i,j} > 0 do
4      P_j ← P_{j,d,k−1,t−1} × (1 − γ)
5      if P_j > P_{i,d,k,t−1} then
6          P_{i,d,k,t} = P_{i,d,k,t} + R_p × M_{i,j} × P_j × (1 − γ)
7          R_p = R_p − R_p × M_{i,j}
8      end
9  end
10 P_{i,d,k,t} = P_{i,d,k,t} + R_p × P_{i,d,k,t−1}
```

When node i meets with another node j, the optimal forwarding decision can be made by simply comparing $\mathcal{P}_{i,d,k,t-1}$ with $\mathcal{P}_{j,d,k-1,t-1} \times (1-\gamma)$ (as shown in Table II). That is, within the same remaining time of $t-1$, if node i has a higher expected delivery rate with k hops than the delivery rate node j can achieve with $k-1$ hops given that the content is successfully transferred to node j with probability $(1-\gamma)$, the optimal decision becomes not to forward the content to node j. Otherwise, forwarding the content to node j will be better on average. Note that this is different than the optimal forwarding strategy presented in [15], [20] as it considers keeping a copy of the content at node i even it will be forwarded to node j, thus, it determines the optimal strategy through cumulative delivery probability of both copies and determines the optimal strategy accordingly. The likelihood of unsuccessful transfer of the content due to link failures is also not considered.

In order to calculate the expected delivery probability, $\mathcal{P}_{i,d,k,t}$, for each node pair (i, d) and different k and t values, the problem can be modeled as a finite horizon optimal stopping problem and can be estimated using backward induction method. That is, we first calculate $\mathcal{P}_{i,d,k,2}$ based on $\mathcal{P}_{i,j,k-1,1}$, $\forall j \neq i, d$ and $\mathcal{P}_{i,d,k,1}$, which can be calculated using (6). Then, we continue calculating $\mathcal{P}_{i,d,k,3}$, $\mathcal{P}_{i,d,k,4}$, and so on.

The calculation of delivery probability $\mathcal{P}_{i,d,k,t}$ under optimal forwarding strategy is shown in Algorithm 1. It is first initialized to direct meeting probability with a potential loss (line 1) and for each node, j, that is different than destination, if forwarding to j is considered better in terms of delivery probability (line 5), the expected increase in delivery probability through node j is added to $\mathcal{P}_{i,d,k,t}$. Note that due to the sparse nature of mobile social networks similar to delay tolerant networks, it is assumed that each node meets one another node at each time slot. Thus, the remaining probability, denoted by R_p, is calculated for each node j, by excluding the meeting probabilities with other nodes considered. Once the estimated probability increase is added from all other nodes, finally, with remaining probability, the probability of delivery from current node with one less remaining TTL value is added (line 10).

In optimal forwarding strategy, as the message is either forwarded or kept entirely, the associated strategy for energy sharing becomes either transfer or keep the entire energy,

Algorithm 2: $P_{i,d,k,t}$ calculation with optimal sharing

1 $P_{i,d,k,t} \leftarrow M_{i,d} \times (1-\gamma)$
2 $R_p \leftarrow 1 - M_{i,d}$
3 **for** $\forall j \in \mathcal{M}$ *s.t.* $j \neq i$ *and* $j \neq d$ *and* $M_{i,j} > 0$ **do**
4 $\quad P_j^* = 0$
5 $\quad (t_i^*, t_j^*) = (t-1, 0)$
6 $\quad (k_i^*, k_j^*) = (k, 0)$
7 $\quad$ **for** $\forall t_i \in [0, t-1)$ **do**
8 $\quad\quad t_j = (t_i - 1) \times e_i / e_j \times \lambda$
9 $\quad\quad$ **for** $\forall k_i \in [0, k-1]$ **do**
10 $\quad\quad\quad k_j = k - 1 - k_i$
11 $\quad\quad\quad P_j = (1-\gamma) \times [1 - (1 - P_{i,d,k_i,t_i}) \times (1 - P_{j,d,k_j,t_j})] + (\gamma) \times P_{i,d,k_i,t_i}$
12 $\quad\quad\quad$ **if** $P_j^* < P_j$ **then**
13 $\quad\quad\quad\quad P_j^* = P_j$
14 $\quad\quad\quad\quad (t_i^*, t_j^*) = (t_i, t_j)$
15 $\quad\quad\quad\quad (k_i^*, k_j^*) = (k_i, k_j)$
16 $\quad\quad\quad$ **end**
17 $\quad\quad$ **end**
18 $\quad$ **end**
19 $\quad$ **if** $P_j^* > P_{i,d,k,t-1}$ **then**
20 $\quad\quad P_{i,d,k,t} = P_{i,d,k,t} + R_p \times M_{i,j} \times P_j^* \times (1-\gamma)$
21 $\quad\quad R_p = R_p - R_p \times M_{i,j}$
22 $\quad$ **end**
23 **end**
24 $P_{i,d,k,t} = P_{i,d,k,t} + R_p \times P_{i,d,k,t-1}$

respectively. However, as sharing can potentially increase the delivery probability, as shown in Fig. 2, the calculation of delivery probability $\mathcal{P}_{i,d,k,t}$ under optimal sharing strategy should consider the split of energy and hop counts with each met node j that can achieve the best delivery probability increase. Algorithm 2 shows this calculation. Lines 7-18 show the process of finding the best TTL split (t_i^*, t_j^*) and hop split (k_i^*, k_j^*) between node i and a met node j that achieves the highest delivery probability, P_j^*. Note that each P_j calculation needs to consider potential loss during transfer thus, with probability γ, P_j is equal to node i's own delivery probability with t_i, k_i pair, while with probability $(1-\gamma)$ it is equal to the cumulative delivery probability with the corresponding optimally split TTL and hop counts, which is defined as

$$1 - (1 - P_{i,d,k_i^*,t_i^*}) \times (1 - P_{j,d,k_j^*,t_j^*}). \tag{7}$$

Once the maximum delivery probability with each neighbor j is found through optimal TTL and hop split, it is compared with individual delivery ratio of node i and if splitting is considered better, it is added to the comprehensive delivery probability of node i, as in the optimal forwarding strategy case. Finally, with remaining probability, R_p, the probability of delivery by current node i with one less remaining TTL value is added.

Table II shows the summary of comparisons that need to be made for a decision under forwarding and sharing cases. Algorithms 1 and 2 show the calculation of $P_{i,d,k,t}$ for these scenarios for a specific (i, d, k, t) tuple. Once it is calculated for every possible tuple following the backward induction order, the actual forwarding or sharing decision can be made by checking these values from the corresponding tables.

Parameter	Value
n	36, 41, 50.
$\mathcal{I}_{i,j}$	Obtained from datasets.
$\mathcal{E}$	16, 8, 8 hours of energy
γ	0.1
λ	0.98
e_i	[0.95, 1.05] units of energy per time slot
L	6 relay nodes
K	4 hops

TABLE III: Simulation settings

IV. Evaluation

In this section, we evaluate the performance of the proposed energy sharing based content delivery process. Next, we first list the algorithms compared, performance metrics used, and describe how the simulations are set. Then, we provide the simulation results and analyze the impact of several parameters on results. The list of the parameters and their values used in simulations are shown in Table III.

A. Algorithms in Comparison

Since energy is used as an incentive to relay nodes to carry the content received from other nodes and defines the time-to-live (TTL) value of the message, we define the algorithms to compare in terms of their impact on the TTL of the message:

- *TTL sharing:* This corresponds to the proposed optimal sharing based strategy obtained with Algorithm 2. TTL is shared with the met node in the amount that will provide the most significant expected benefit in delivery ratio.
- *TTL forwarding:* This corresponds to the optimal forwarding strategy obtained with Algorithm 1. TTL is either fully forwarded (with loss) to the met node or kept fully depending on whichever provides higher expected delivery ratio.
- *TTL spraying:* This is a modified version of well-known Spray-and-Wait [18] algorithm within the context of energy and TTL sharing based delivery. Source node distributes the message to L different relay nodes (who can directly meet with destination[2]) together with its $1/L$ of initial TTL budget. If the remaining TTL budget is less than that, the entire remaining TTL is forwarded.

B. Performance Metrics

We use the following metrics in the performance comparison of the aforementioned algorithms:

- *Average delivery rate:* This is the ratio of the number of messages delivered to the destination node within all messages generated before the TTL budget expires.

[2]This is considered in order to increase the likelihood of delivery. However, if there is no such node, it is not considered.

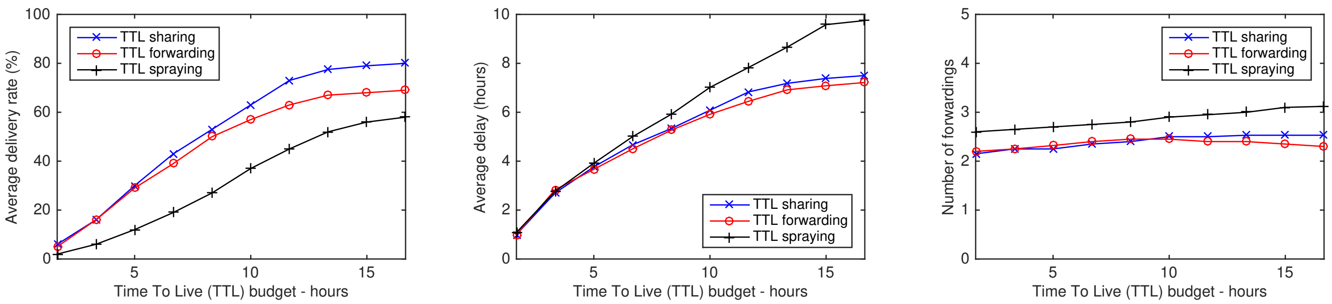

Fig. 3: Delivery rate, delay and number of forwardings versus time-to-live in Cambridge dataset.

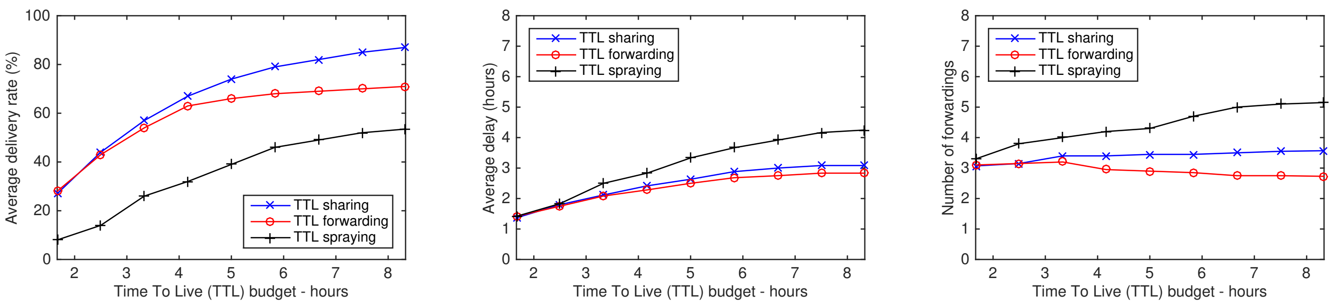

Fig. 4: Delivery rate, delay and number of forwardings versus time-to-live in Haggle dataset.

- *Average delivery delay:* This is the average of elapsed time between the delivery of the messages and their generation at the source nodes. It is the average of delivery delays of only delivered messages before the TTL budget expires.
- *Number of forwardings:* This is the number of times a message is exchanged between two nodes before the delivery of the message.

C. Datasets

We use two of the commonly used real DTN traces [41] for routing performance evaluation. Moreover, we also generate our own synthetic dataset to have a more dense connectivity graph with sufficient meeting history. Each of these datasets represents a different environment with a different number of users and duration:

- **Cambridge dataset:** These are the Bluetooth recordings among 36 students with iMotes from Cambridge University for a duration of almost two months.
- **Haggle dataset:** These are the Bluetooth sightings recorded between the iMotes carried by 41 attendants of Infocom Conference held in Miami in 2005. It spans a four day period.
- **Synthetic dataset:** This is a dataset generated randomly among 50 nodes with a mean intermeeting time of a random value between [200, 400] minutes. The nodes have a meeting history on average with 10 different nodes.

In today's technology, mobile nodes should be in close proximity (i.e., almost touching) to be able to transfer power. While the Bluetooth (which is considered in above real traces) communication range is in the order of several meters, such interactions can be considered as an indication of users being in the close proximity of each other so that they can communicate and get further close to each other for a potential energy transfer. We assume that when nodes meet, they stay close enough to each other until they can achieve the required energy transfer under optimal *TTL sharing* scenario. We look at the impact of transfer efficiency in our results, which can be considered as the relaxation of this assumption to some extent. However, in our future work, we will enhance our algorithm considering the partial energy transfers between nodes during meetings with limited duration.

D. Performance Results

In Fig. 3, we first compare the performance of the three algorithms in the Cambridge dataset. In order to see the benefit of the sharing based delivery, source and destination pairs are selected such that they do not directly meet. *TTL sharing* offers the best delivery rate among all algorithms. Moreover, it can achieve this with a similar average delivery delay and a similar number of forwardings with *TTL forwarding*. There is a slight increase in the number of forwardings with larger TTL budgets. This is due to the increased delivery ratio achieved at those TTL budgets.

The results for Haggle traces are illustrated in Fig. 4. We observe similar performance graphs, but the gap in the number of forwardings of *TTL sharing* and *TTL forwarding* is more

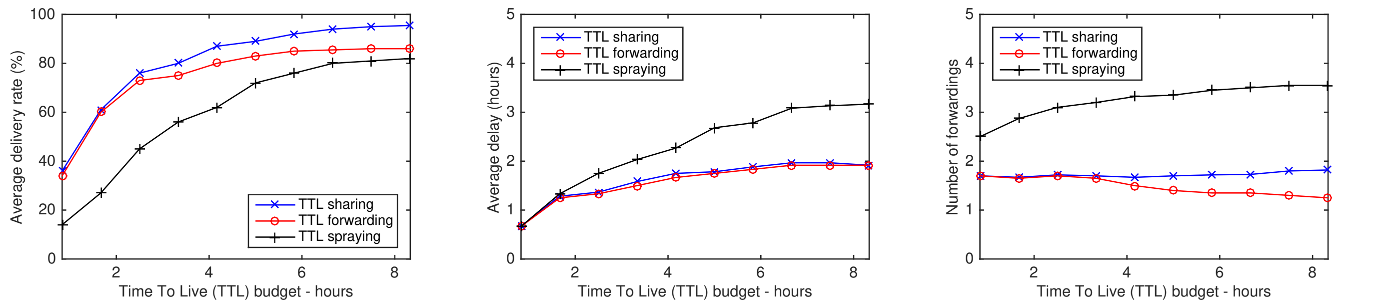

Fig. 5: Delivery rate, delay and number of forwardings versus time-to-live in synthetic dataset.

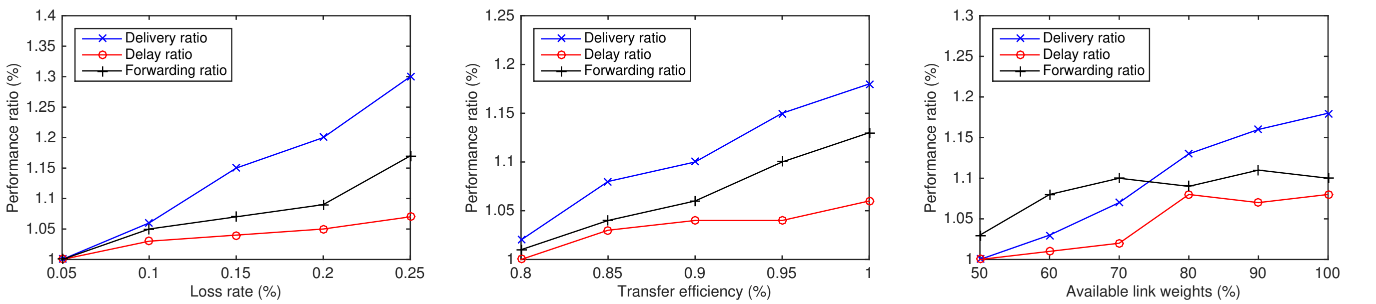

Fig. 6: Impact of loss rate, transfer efficiency and available partial link weight on the performance ratio of sharing over forwarding.

and starts in earlier TTL budgets. On the other hand, it is still less than the *TTL spraying* algorithm and achieves the best delivery ratio. Note that such a performance improvement in the delivery ratio can be preferred as the forwarding cost per message delivery is a small value.

In Fig. 5, we look at the performance results with synthetic dataset. The results are also similar to other dataset results but the delivery ratios of *TTL sharing* and *TTL forwarding* is closer to each other. This is because the benefit of sharing policy could be dominated with other optimal forwarding based paths which could appear more often in dense graphs.

Finally, we look at the impact of some parameters in the performance results. In Fig. 6, we plot the impact of loss rate, transfer efficiency and partially available link weight information on the performance ratio of the *TTL sharing* compared to *TTL forwarding*. As the results show, with increasing loss rates, the benefit of sharing is more pronounced as it can provide better delivery probability over multiple paths (despite the shorter TTL in each due to the split). However, this also increases the forwarding ratio which can be an issue if there is not enough buffer at nodes. On the other hand, as loss rate gets smaller, the performance ratio gets close to 1. Transfer efficiency also affects the performance ratio of the *TTL sharing* remarkably. As the efficiency gets lower, *TTL sharing* behaves like *TTL forwarding*, meaning sharing is not considered beneficial due to the loss during energy transfers. Finally, in the last graph, the impact of partially available intermeeting time information on the results is shown. For these results, we set the $\mathcal{I}_{i,j}$ values for some pairs to 0 (i.e., unknown) and calculate the $P_{i,d,k,t}$ values accordingly. The results show that when 50% of the link weights or mean intermeeting times are unknown, the benefits over *TTL forwarding* are lost. Thus, this suggests that the proposed optimal sharing policy will be more effective in networks with long-term stable relations among nodes with predictable meeting patterns.

V. Conclusion

In this paper, we study the content delivery problem in mobile social networks in which nodes are motivated by energy transfers for carrying the messages. That is, each relay node carries a message forwarded by another node as long the energy provided or the corresponding time-to-live (TTL) value lasts. In order to find the optimal content and energy forwarding or sharing policy, we model and solve the problem using optimal stopping theory and dynamic programming. We evaluate the performance of the proposed solution in both real and synthetic mobile social network traces and show that sharing can offer better delivery rate, while it can also cause an increase in the cost of delivery (i.e., number of forwardings) to some extent. We also look at the impact of several parameters on the performance of the proposed sharing based content delivery process and discover the settings that provide performance enhancements.

In our future work, we will analyze the performance of the proposed system in other datasets as well as work on the closed-form expression to reduce time dimension as in [20].

We will also study the partial energy transfers during meetings with limited duration between nodes in which the split of the content can also be considered.

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