On Optimality of Routing Policies in Delay-Tolerant Mobile Social Networks

Neetya Shrestha and Lucile Sassatelli
Laboratoire I3S - Université Nice Sophia Antipolis - CNRS UMR 7271 - 06903 Sophia Antipolis, France
Email: {shrestha,sassatelli}@i3s.unice.fr

***Abstract*—In Delay Tolerant Networks (DTN), contemporaneous end-to-end paths are rarely available. Routing in such networks is therefore one of the challenging issues. When the DTN is made of humans, human mobility characterizes the forwarding opportunities. To leverage the diversity of the strengths of social ties, a number of utility-based routing policies have been proposed. In this paper we first address theoretically the optimization problem of the routing policy in such a social DTN, under a multi-community network model, and we prove that the optimal policies have a per-community threshold structure, thereby generalizing the existing works for homogeneous mobility DTN. We then provide analysis of this result on a numerical example, and discuss the comparison of such optimal policies with the online utility-based policies of the literature.**

I. Introduction

Delay Tolerant Networks (DTNs) are sparse Mobile Ad-hoc NETworks (MANETs) where there is no guarantee that a path exists between source and destination at any instant of time. The reasons for sparsity can be short radio range so as to avoid interference, obstruction or intermittent sleeping mode. Owing to the intermittent connectivity, the nodes must rely on the Store-Carry-and-Forward paradigm which inherently entails delay for communication. That is the reason why such sparse MANET are referred to as Delay Tolerant Networks (DTN). Examples of such networks include Pocket Switched Networks (PSNs) based on human mobility [1] or vehicular networks (VANETs) based on public bases or taxicabs. To lower the delivery delay, multiple copies of the same packet can be spread. How to spread multiple copies has been investigated in several proposals. Epidemic routing [2] has been proposed to flood data packets to all nodes in the network, sparing the maximum of energy to minimize the delay. However, most mobile nodes in DTNs have limited energy and may prefer fewer transmissions to prolong network lifetime. For these reasons, probabilistic routing [3] and Spray-and-Wait [4] are proposed to achieve trade-offs between network resource consumption and protocol performance. The DTN of interest in this paper are social DTN made of people carrying portable devices [1]. Human mobility exhibit heterogeneous patterns where node clustering into communities arises owing to social relationships [5]. To leverage the diversity of the strengths of social ties, a number of online utility-based routing policies discussed below have been proposed.

This paper aims at identifying the structure of optimal routing policies, given a multi-community network model, and then assess the distance to optimal policy of some utility-based routing policies.

Contributions: Our contributions are threefold:

- From a multi-community network model, based on mean-field approximations leading to a fluid model of the dissemination process, we formulate the problem of finding the time-dependent forwarding probabilities between any two communities to maximize the delivery probability by a certain deadline under a given constraint of energy.
- We prove that optimal forwarding policies are per-community threshold policies. We provide a numerical illustration by using a heuristic optimization algorithm.
- We discuss the comparison of the main existing decentralized utility-based routing policies to the optimal policy, so as to assess the distance of these practical routing policies to the optimal in terms of the underlying network social structure.

Related works: Two kinds of works are related to ours: the study of what are the best nodes to give the packet to, i.e., that of optimal routing policies, and the design of decentralized utility-based routing policies relying on a smart choice of the utility criterion.

The first set of works include [6], [7] and [8]. In [7], Picu and Spyropoulos consider multicast traffic and identify the best relays to carry the L copies of a packet so as to minimize the maximum time for a destination to retrieve a copy (L is an upper-bound on the number of copies allowed to spread in the network). To do so, they assume that the available knowledge (centralized at an oracle) is only the degree of each node, i.e., the number of different nodes a node meets within a time window. To go from the set of nodes' degrees to the set of probability of contact between any two nodes, they build on the assumption that the probability of meeting between nodes i and j is proportional to both degrees of i and j, coming from the configuration model [7]. Doing so, they come up with the result that the L best relays to carry the L copies are are those with the highest degrees. Then, in [8], the same authors present a Markov Chain Monte Carlo (MCMC) algorithm as a distributed solution for online placement to the above defined relays. Our work differs from [7] and [8] in that we consider unicast traffic, and we do not make such assumption on the network connectivity but only assume that the nodes are clustered into communities into which the nodes have the same mobility features, following the model of [9]. Some communities may be "hub" communities, meaning that they can often act as relays between other communities. This allows us to define, in a centralized manner for theoretical purpose, not only what are the communities that must receive the L copies of a packet and how many nodes must be infected in each community, but also what are the paths these copies must follow. These parameters are hence dependent on the communities of the source and destination nodes of the unicast session. In [6], Altman et al. consider a homogeneous network defined by the number of nodes and the mean inter-meeting time between any pair of nodes. For probabilistic forwarding in two-hop and epidemic routing, they formulate the optimal control problem, based on a fluid model of the system's dynamics, to minimize the delay under some energy constraint. In particular, they show that the time-dependent problem is optimized by threshold type policies. In this paper, we extend the work of [6] to identify the structure of optimal routing policies that account for the social features of real-world scenario, i.e., a multi-community environment with heterogeneous mobility.

On the other hand, a number of routing policies have been proposed for DTNs to improve the trade-off between performance and energy (or memory) consumption by accounting for the social features of PSN. Their principle is not to spend the allowed number of transmissions with the first met nodes (in a greedy manner), but instead to smartly choose the relays to give the copies to. Owing to lack of space, we do not provide a review of these main routing techniques, but rather mention them before detailing the policies we use in Section IV. We can cite MaxProp [10], BubbleRap[11], PeopleRank [12] and SimBet [13]. Other similar utilities were investigated in [14]: Last-Seen-First (LSF), Most-Mobile-First (MMF) and Most-Social-First (MSF).The same multi-community model as ours is considered, and a fluid model of the network dynamics is used to prove that the utility-based replication (MMF) achieves a lower delivery delay than a greedy-based replication. However, they do not investigate the optimality of forwarding policies based on such model, as we do in this paper. As well, Bulut et al. [15] studied the effects on the performance of multi-copy based two-hop routing algorithm under the same model. However, they limit the analysis to only two communities. We formulate and address the problem in a more general case. The rest of the paper is organized as follows. Section II presents the network model and the mean-field approximation. In Section III, we present the theoretical analysis of the optimization problem and the results on the structure of optimal policies. In Section IV we discuss the comparison of the optimal routing policies to some decentralized utility-based policies. Section V concludes the paper.

II. Network model

We use the heterogeneous mobility model considered in [14], [15]: the network is made of N mobile nodes divided into M communities (possibly centered around home-points). The number of nodes in community i is N_i, and we assume that a node pertains to only one community. We denote the total number of nodes by $N = \sum_{i=1}^{M} N_i$, and consider the node partition vector $\mathbf{N} = (N_1, \ldots, N_M)$. The time between contacts of any pair of nodes of communities i and j is exponentially distributed [16] with mean $1/\beta ij$, where β_{ij} is the inter-meeting intensity defined as the mean number of meetings per time unit between a given node of community i and a given node of community j, and we assume that $\beta_{i,i} > \beta_{ij}$, for $i \neq j$, for all $i, j \in \{1, \ldots, M\}$. Let β be the matrix storing the $\{\beta_{ij}\}_{i,j=1}^{M}$. The scenario under study is a source node S of community c_s that wants to send a message (or packet) to a destination node of community c_d. The multi-packet case is part of future work. We consider a unicast session without background traffic. Let τ be the delivery deadline until which the message is relevant to the destination. For the sake of lighter notation, a node of community i is denoted as i-node.

Let $\hat{X}_i^{(\mathbf{N})}(t)$ be the fraction of i-nodes (over N) that have a copy of the message at time t. Let $\hat{X}^{(\mathbf{N})}(t) = \sum_{i=1}^{M} \hat{X}_i^{(\mathbf{N})}(t)$. Let $\mathbf{u}(t)$ be the policy controlling the message spreading: $u_{ij}(t)$ is the probability that a j-node gives the packet to a i-node when they meet.

Mean-field approximations: We build on [17], [18] and consider time t sampled over the discrete domain, i.e., $t \in \mathbb{N}$. The expected change in the number of infected i-nodes in one time slot is defined by

$$f_i^{(\mathbf{N})}(\mathbf{m}) = E\left[\hat{X}_i^{(\mathbf{N})}(t+1) - \hat{X}_i^{(\mathbf{N})}(t)) \mid \hat{\mathbf{X}}^{(\mathbf{N})}(t) = \mathbf{m}\right] .$$

In our model, we have $f_i^{(\mathbf{N})}(\mathbf{m}) = \sum_{j=1}^{M} u_{ij}(t)\beta_{ij}N_j m_j(\frac{N_i}{N} - m_i)$. When N tends to infinity, as we consider a sparse network where the density remains constant when the total number of nodes increases (the ratios N_i/N, for all $i = 1, \ldots, M$, keep constant), $\lambda_{ij} = \beta_{ij}N_j$ remains constant in N. Therefore, for all $i = 1, \ldots, M$:

$$\lim_{N\infty} f_i^{(\mathbf{N})}(\mathbf{m}) = \sum_{j=1}^{M} u_{ij}(t)\lambda_{ij}m_j(\frac{N_i}{N} - m_i)$$

that is independent of N. Then Theorem 3.1 of [17] ensures that the process $\hat{\mathbf{X}}^{(\mathbf{N})}(t)$ converges to a deterministic process $\mathbf{X}(t) = (X_1(t), \ldots, X_M(t))$ which is the solution of the Ordinary Differential Equation (ODE):

$$\forall i = 1, \ldots, M, \quad \frac{dX_i(t)}{dt} = \sum_{j=1}^{M} u_{ij}(t)\lambda_{ij}X_j(t)(\frac{N_i}{N} - X_i(t)),$$

where $X_{c_s}(0) = z$ and $X_i(0) = 0$ for $i \neq c_s$. The above equation is referred to as the fluid model (or mean-field limit) of the dissemination process.

Let D_{c_s,c_d} be the random variable describing the time of delivery. As well, we can derive the fluid limit $P_{c_s,c_d}(\tau)$ of the cumulative distribution function (CDF) of the delay (we assume that the probability that a node gives the packet to the destination node upon meeting is 1): $\frac{dP_{c_s,c_d}(t)}{dt} = \sum_{j=1}^{M} \lambda_{c_d j} X_j (1 - P_{c_s,c_d}(t))$, whereby:

$$P_{c_s,c_d}(\tau) = 1 - \exp^{-\int_0^\tau \sum_{j=1}^{M} \lambda_{c_d j} X_j(t) dt} . \qquad (1)$$

III. Optimization results

In this section, we first express the problem of optimizing the routing policy $\mathbf{u}(t) = \{u_{ij}(t)\}_{i,j=1}^{M}$ subject to an energy constraint, and secondly, we derive the structure of the optimal routing policies for a given optimization problem. For the sake of clarity, let $X_i(t)$ turn to be the number of i-nodes infected by the message, for all $i = 1, \ldots, M$. We consider that the energy consumed by the whole network from time 0 up to τ is proportional to the total number of transmissions that occurred within this time interval. As we do not consider any buffer cleaning mechanism, the energy is hence proportional to $X(\tau) - X(0)$. Let $\epsilon(\tau)$ be defined as this total number of transmissions: $\epsilon(\tau) = X(\tau) = \sum_{j=1}^{M} X_j(\tau)$. Enforcing an energy constraint therefore consists in finding a policy $\mathbf{u}(t)$ such that $\epsilon(\tau) \leq E$, where E is given by the problem.

A. The optimization problem with an energy constraint

We consider the following constrained optimization problem (CP): [Find $\mathbf{u}(t)$ that maximizes $P_{c_s,c_d}(\tau)$ subject to $\epsilon(\tau) \leq E$].
From eq. (1), problem (CP) is equivalent to maximize $J_{c_s,c_d}(\tau, \mathbf{u}(t)) = \int_0^\tau \sum_{j=1}^{M} \beta_{c_d j} X_j(t) dt$. Expressing $J_{c_s,c_d}(\tau, \mathbf{u}(t))$ as $J_{c_s,c_d}(\tau, \mathbf{u}(t)) = \sum_{j=1}^{M} \beta_{c_d j} \int_0^\tau X_j(t) dt$, we can see that problem (CP) is a linear optimization problem in the $\int_0^\tau X_j(t)dt$, for $j = 1, \ldots, M$, but a non-linear optimization problem in $\mathbf{u}(t)$.

B. The structure of optimal routing policies

Although the optimization problem (CP) is non-linear, we are able to identify the subset of policies the optimal policies belong to: below is presented the way to the main result of the paper, that is the per-community threshold structure of optimal policies.

Definition 3.1 (Condition (C)): A policy $\mathbf{u}(t)$ verifies condition (C) if and only if there exists a couple of indexes (I, j) with $0 < u_{Ij}(t) < 1$ for some non-empty interval $[a, b] \subset [0, \tau]$. Let $C(\mathbf{u}(t)) = I$ denote the former I index.

Definition 3.2: Consider a policy $\mathbf{u}(t)$ verifying condition (C) and $X(\tau) \leq E$. We define a threshold policy $\bar{\mathbf{u}}(t)$ obtained from $\mathbf{u}(t)$ by the following procedure:

- Initialization: $I = C(\mathbf{u}(t))$
- Recursion: Do$\{$
  $\bar{\mathbf{u}}(t) =$output of atomic step with input $(\mathbf{u}(t), I)$
  $I = C(\bar{\mathbf{u}}(t))$
  $\mathbf{u}(t) = \bar{\mathbf{u}}(t)$
  $\}$while($\bar{\mathbf{u}}(t)$ satisfies condition (C))
- Atomic step: Let $\mathbf{X}(t)$ be the state process under policy $\mathbf{u}(t)$, and $\bar{\mathbf{X}}(t)$ that under policy $\bar{\mathbf{u}}(t)$.
  We first take, for all $i, j = 1, \ldots, M$:

$$\bar{u}_{ij}(t) = \begin{cases} u_{ij}(t) & \text{, if } i \neq I \\ 1 & \text{, if } i = I \text{ and } t \leq t_I \\ 0 & \text{, if } i = I \text{ and } t > t_I \end{cases}$$

where t_I is such that $\bar{X}_I(\tau) = \bar{X}_I(t_I) = X_I(\tau)$. Then appropriately threshold all $\bar{u}_{ij}(t)$ for $i \neq I$:

$$\bar{u}_{ij}(t) = \begin{cases} u_{ij}(t) & \text{, if } i \neq I \text{ and } t \leq t_i \\ 0 & \text{, if } i \neq I \text{ and } t > t_i \end{cases}$$

where t_i is such that $\bar{X}_i(\tau) = \bar{X}_i(t_i) = X_i(\tau)$.

Lemma 3.1: Let the success probability for policy $u_{ij}(t)$ be $P_s(\tau)$ and that for policy $\bar{u}_{ij}(t)$ be $P'_s(\tau)$. Then: (i) $\bar{u}_{ij}(t)$ satisfies the energy constraint $\bar{X}(\tau) \leq \tau$, and (ii) $P'_s(\tau) > P_s(\tau)$.
Proof: (i) By construction of the improvement procedure of definition (3.2). (ii) By construction, each of the atomic steps generates $\bar{X}_i(t) \geq X_i(t)$ and $\bar{X}_i(\tau) = X_i(\tau)$ for all $i = 1, \ldots, M$, and $\bar{X}_I(t) = X_I(t)$ for $t \in [a, b]$ (Def. 3.2, whereby the result $P'_s(\tau) > P_s(\tau)$. ⋄

Theorem 3.1: An optimal policy for problem (CP) is a per-community threshold policy, i.e., has the following structure: for all $i, j = 1, ..., M$, there are thresholds $s_i \in [0, \tau]$ for which, for all $j = 1, \ldots, M$, $u_{ij}(t) = 1$ for $t \in [0, s_i]$ and $u_{ij}(t) = 0$ for $t > s_i$.
Proof: Let $\mathbf{u}(t)$ be an arbitrary policy which satisfies the energy constraint but is not a threshold policy as defined above. Then, there exists some couple (i, j) and some non-empty interval $[a, b] \subset [0, \tau]$ on which $0 < u_{ij}(t) < 1$. So $\mathbf{u}(t)$ can be strictly improved according to Lemma 3.1. Hence, $\mathbf{u}(t)$ is not optimal. ⋄
This theoretical result means that, given the β and $\mathbf{N}$ parameters, the optimal number of copies to spread in each community is decided by the optimization solution, and the way to spread those copies is the fastest as possible, that is, for each community i, in an epidemic way from any communities j until s_i, i.e., until the number of copies is reached. This is in accordance with the results in the case of homogeneous DTN, where [6], [4] showed that threshold-policies or Spray-and-Wait, are the best in terms of mean delivery delay under an energy constraint. It is worth noticing that the so-called optimal policies, obtained from the optimization of problem (CP), are offline policies.

C. Example of numerical optimization

Thanks to the differential evolution algorithm [19], a numerical heuristic optimization method, we analyze the resulting optimal threshold policy on a toy-example in which there are $M = 3$ communities, the number of nodes in each community is $\mathbf{N} = (33, 33, 34)$, the β matrix is given below:

$$\beta = \begin{bmatrix} 0.2 & 0.1 & 0.05 \\ 0.1 & 0.4 & 0.1 \\ 0.05 & 0.1 & 0.3 \end{bmatrix}.$$

We set the community of the source and destination to $c_s = 1$ and $c_d = 3$, and the deadline $\tau = 0.7$ for which $P_s(\tau)$ is the objective to maximize. Let h_{ji} for all $i, j = 1, \ldots, M$ be the time threshold up to when a j-node gives a i-node a copy upon meeting, and stops doing so thereafter. Table I shows the optimized time thresholds h_{ji}, TX_{ij} which is the total number of transmissions from community i to community j by time

E	$h_{i,j}$			TX_{ij}			TX
100	0.695	0.682	0.673	17	5	4	97
	0.678	0.680	0.696	10	23	9	
	0.688	0.679	0.678	4	4	21	
40	0.127	0.252	0.501	1	2	1	40
	0.098	0.245	0.581	0	7	6	
	0.137	0.219	0.505	0	1	22	
10	0.132	0.063	0.325	1	0	1	9
	0.119	0.080	0.296	0	0	0	
	0.106	0.018	0.332	0	0	7	

TABLE I
ANALYSIS OF THE OPTIMAL THRESHOLD POLICY.

τ, and the total number of transmissions to be compared with E. We have $TX_{ij} = \int_0^\tau \beta_{i,j} u_{i,j}(t) X_i(t)(N_j - X_j(t))dt$ and $TX = \sum_{i,j=1}^M TX_{ij}$. Let us first comment the h_{ji} values. Theorem 3.1 states that the h_{ji}, for given i and all $j = 1, \ldots, M$, must be equal (to the per-community threshold s_i). In the optimization procedure, the h_{ji} are the output shown in Table I. They can be set independently, and they appear to be almost constant per column, as predicted by Theorem 3.1. Only the second column for $E = 10$ exhibits significant differences, but they do not impact the number of transmissions received in the second community, that keeps 0. Let us now comment the TX_{ij} values, that allow easier interpretation of the thresholds by making appear the sharing of the energy budget across the communities. When the maximum number of copies is highly constrained ($E = 10$), it is better for the source to give a copy to community c_d, and to let the allowed number of copies be fully allocated to spreading inside c_d. However, when the allowed number of copies E increases to 40, then some spare copies, additionally to that in the destination, are worthy spreading in community 2 because the β matrix shows that community 2 has a higher meeting rate with $c_d = 3$ than $c_s = 1$ has.

IV. Distance from Optimality of Decentralized Utility-Based Policies

After having theoretically identified the structure of (offline) optimal policies and derived the numerical optimization, now we compare the existing online utility-based policies to the optimal ones, so as to analyze in what cases we can expect these solutions will perform relatively close to, or far from, the optimal policy.

Main classes of utility-based policies have been summarized in [14]. Each node $i = 1, \ldots, N$ maintains a utility function $U_i(j)$ for each other node j. If node i, carrying a copy of the packet destined to node d, has $r > 1$ forwarding tokens and encounters node j with no copy, then i decides to give a copy to j based on the following rules: (i) if $U_j(d) > U_i(d)$ (R1) or (ii) if $U_j(d) > U_{th}$ for some threshold value U_{th} (R2). For example the so-called *Last-Seen-First* (LSF) policy is such that $U_i(j) = \frac{1}{1+\tau_i(j)}$ where $\tau_i(j)$ is the time elapsed since the nodes i and j last encountered each other.

For the purpose of comparison of utility-based policies to the optimal policies devised in Section III, consider the multi-community network model of Section II. Let c_i and c_j be the communities of nodes i and j, respectively. Let us consider the LSF policy. The inter-meeting time between i and j is exponentially distributed with mean $\frac{1}{\beta_{c_i c_j}}$. The expectation of $U_i(j)$ can be computed rigorously and is equal to $E[U_i(j)] = \beta_{c_i c_j} e^{\beta_{c_i c_j}} \Gamma(0, \beta_{c_i c_j})$, where $\Gamma(0, \beta_{c_i c_j})$ is the upper incomplete Gamma function. Consider the approximation of $E[U_i(j)]$ by $\beta_{c_i c_j}$, valid for low $\beta_{c_i c_j}$.

Considering rule (R1), the fluid model for optimal threshold policy and utility-based policy are as follows:

$$\frac{dX_k(t)}{dt} = (N_k - X_k(t)) u_k(t) \sum_{l=1}^M \beta_{kl} X_l(t)$$

for optimal threshold policy where, $u_{ij}(t)$ turns to be independent of i according to Theorem 3.1, and

$$\frac{dX_k(t)}{dt} = (N_k - X_k(t)) \sum_{l:\beta_{lc_d} > \beta_{kc_d}} \beta_{kl} X_l(t), \text{ until } X(t) = E$$

for utility-based policy with rule (R1).

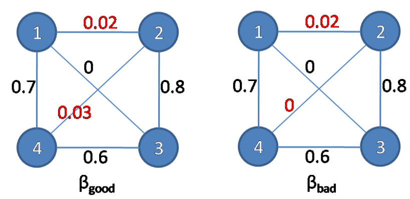

Fig. 1. Graphs of communities connections corresponding to two β matrices.

Fig. 2 shows the CDF of the delivery delay both for LSF and the optimal policies, for two β matrices, with $M = 4$ communities, $N/4 = 25$ nodes per community, $c_s = 1$ and $c_d = 2$. The simulations are done by averaging over 200 runs for each point, and the contact traces for each β matrix have been generated synthetically based on exponentially distributed inter-meeting times. The confidence intervals are not plotted for the sake of visibility, but the differences are statistically significant. As expected, the performance of LSF is worse than that of the optimal policy, as the latter assumes full knowledge of the network topology, whereas the former learns the graph topology from the encounters. The question that arises is therefore whether the gap between LSF and optimal is only due to the absence of assumption on the network topology for LSF, or also to the very definition of the utility done in LSF. To answer this question, Fig. 2 also shows the performance of "LSF steady" which denotes the LSF policy where the utility $U_i(j)$ is set to β_{ij} from the beginning, so as to lift the impact of utility convergence on the difference between LSF and optimal. We observe from Fig. 2 that such impact either fully explains the difference (for β_{Good}) or only partly (for β_{Bad}). Indeed in utility-based routing, the packet can be disseminated only from source community c_s to successive communities $i_1, i_2, \ldots$ with $\beta_{sd} < \beta_{i_1 d} < \beta_{i_2 d}$ (in a so-called gradient-based manner) until packet reaches destination. Doing so, some low-delay paths from the source to the destination can be missed by the LSF policy. For example, let us consider the two toy-examples in Fig. 1 with $c_s = 1$ and $c_d = 2$. The performance is shown in Fig. 2. The LSF policy is expected to perform well on $\beta_{\mathbf{Good}}$ and bad on $\beta_{\mathbf{Bad}}$, as in the latter case, LSF will not allow the packet to get to community 4, and hence to travel along the low-delay path $1-4-3-2$, contrary to the optimal policy.

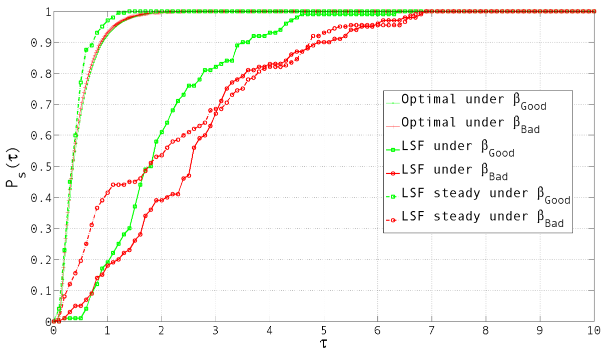

Fig. 2. CDF of the delivery delay, under $L = E = 10$.

Community	1	2	3	4
β_{Good}	1.74	2.65	1.61	0.640
β_{Bad}	2.03	3.48	1.19	0

TABLE II
MEAN NUMBER OF TRANSMISSIONS IN EACH COMMUNITY BY THE LSF POLICY, UNDER $E = 10$.

Utility-based policy based on order-2 neighbors can perform better than LSF on network configurations such as β_{bad}. That is the case of Prophet [3], that uses history of encounters , and the utility value is updated with the transitivity property. This feature brings Prophet closer to the optimal routing than LSF is, at the expense of complexity. In MaxProp [10], each node i keeps the record of the meeting rate with node j, f_j^i, for all $i, j = 1, \ldots, M$ (that is similar to β_{ij} estimations) of each path towards destination and selects the best path, in terms of delivery likelihood, to forward the packet. It therefore tries to approach the optimal solution. However, these two routing algorithms work with a single copy. In BubbleRap [11], each node keeps the record of its community label, its local rank and its global rank. Local rank and global rank are based on betweenness centralities estimated by the number of different nodes met within a time window inside and outside the node's community, respectively. Such parameters imply a different model than the multi-community model presented in Section II, which does not allow to distinguish between nodes inside the same community. Therefore the global rank can be expressed thanks to the multi-community model, but the local rank will be the same for all the same community nodes. The multi-community model does not encompass such possibility for the sake of simplicity, so as to be able to derive theoretical results on optimal routing policies as done in Section III, then to compare with existing online utility-based policies.

V. CONCLUSION

In this paper we have addressed the problem of optimizing routing policies in mobile social DTN. Thanks to a mean-field approximation of the spreading process, we have formulated the problem of finding the optimal time-dependent policies under a given constraint of energy. We have proven theoretically that the optimal policies are per-community threshold policies, and we have discussed the distance to optimal of online utility-based polices of the literature. As future work, we plan to address the case where the message is split over several data packets, where communities can overlap, and in particular, based on the obtained results, we intend to study new routing schemes where the number of copies delivered to each node is a function of the utility value of this node, so as to generalize the utility-spraying presented in [14] (Def. 3.2).

REFERENCES

[1] P. Hui, A. Chaintreau, J. Scott, R. Gass, J. Crowcroft, and C. Diot, "Pocket switched networks and human mobility in conference environments," in *Proc. of ACM SIGCOMM workshop on DTN*, Philadelphia,USA, Aug 2005, pp. 244–251.

[2] A. Vahdat and D. Becker, "Epidemic routing for partially-connected ad hoc networks," in *Tech. Rep. CS-200006*, Duke University, 2000.

[3] A. Lindgren, A. Doria, and O.Schelén, "Probabilistic routing in intermittently connected networks," *SIGMOBILE Mob. Comput. Commun. Rev.*, vol. 7, no. 3, pp. 19–20, Jul. 2003.

[4] T. Spyropoulos, K. Psounis, and C. Raghavendra, "Efficient routing in intermittently connected mobile networks: the multi-copy case," *IEEE/ACM Trans. Netw.*, vol. 16, no. 1, pp. 77–90, Feb 2008.

[5] T. Hossmann, T. Spyropoulos, and F. Legendre, "A complex network analysis of human mobility," in *IEEE NetSciCom 11 (co-located with IEEE Infocom 2011)*, Shanghai, China, 2011.

[6] E. Altman, T. Basar, and F. D. Pellegrini, "Optimal monotone forwarding policies in delay tolerant mobile ad-hoc networks," *Performance Evaluation*, vol. 67, no. 4, p. 299–317, 2010.

[7] A. Picu and T. Spyropoulos, "Minimum expected *-cast time in DTN," in *Proc. of BIONETICS*, Avignon, France, Dec 2009, pp. 103–116.

[8] ——, "Distributed stochastic optimization in opportunistic networks: The case of optimal relay selection," in *ACM CHANTS 2010*, Chicago, IL, USA, Sep 2010.

[9] M. Garetto, P. Giaccone, and E. Leonardi, "Capacity scaling of sparse mobile ad hoc networks," in *Proc. of IEEE INFOCOM*, Phoenix, AZ,USA, Apr 2008, pp. 206–210.

[10] J. Burgess, B. Gallagher, D. Jensen, and B. Levine, "Maxprop: Routing for vehicle-based disruption-tolerant networks," in *Proc. of IEEE INFOCOM*, vol. 10, Barcelona, Spain, Apr 2006, pp. 1–11.

[11] P. Hui, J. Crowcroft, and E. Yoneki, "Bubble rap: Social-based forwarding in delay tolerant networks," *IEEE Trans. on Mob. Comp.*, vol. 10, no. 11, pp. 1576 – 1589, Nov 2011.

[12] A. Mtibaa, M. May, C. Diot, and M. Ammar, "Peoplerank: Social opportunistic forwarding," in *Proc. of IEEE INFOCOM*, San Diego, CA, USA, Mar 2010, pp. 1–5.

[13] E. Daly and M. Haahr, "Social network analysis for information flow in disconnected delay-tolerant MANET," *IEEE Trans. on Mob. Comp.*, vol. 8, no. 5, pp. 606 – 621, May 2009.

[14] T. Spyropoulos, T. Turletti, and K. Obraczka, "Routing in delay-tolerant networks comprising heterogeneous node populations," *IEEE Trans. on Mob. Comp.*, vol. 8, no. 8, pp. 1132 – 1147, Aug. 2009.

[15] E. Bulut, W. Zijian, and B. Szymanski, "Impact of social networks in delay tolerant routing," in *IEEE GLOBECOM 2009*, Honolulu, HI, USA, Dec 2009, pp. 1–6.

[16] R. Groenevelt, P. Nain, and G. Koole, "The message delay in mobile ad hoc networks," *Perform. Eval.*, vol. 62, no. 1-4, pp. 210–228, Oct. 2005.

[17] T. G. Kurtz, "Solutions of ordinary differential equations as limits of pure jump markov processes," *Journ. of Appl. Prob.*, vol. 7, no. 1, pp. 49–58, Apr 1970.

[18] X. Zhang, G. Neglia, J. Kurose, and D. Towsley, "Performance modeling of epidemic routing," *Comput. Netw.*, vol. 51, no. 10, pp. 2867–2891, Jul. 2007.

[19] K. Price and R. Storn, "Differential evolution – a simple and efficient heuristic for global optimization over continuous spaces," *Journ. of Glob. Optim.*, vol. 11, pp. 341–359, 1997. [Online]. Available: http://www1.icsi.berkeley.edu/~storn/code.html