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Abstract. Opportunistic networks are one of the most promising evolutions of the traditional Mobile Ad Hoc Networks paradigm. Communications in an opportunistic network rely on the mobility of the users: each message is handed over from node to node, making hop-by-hop decisions to select the node that is better suited for bringing the message closer to its destination. Algorithms exploiting social-awareness are emerging as one of the most efficient categories of forwarding algorithms. However we are currently lacking analytical models able to characterize the performance of social-aware forwarding in opportunistic networks. In this paper we start to fill this gap by proposing an analytical model for the expected number of hops and the expected delay experienced by messages when delivered in an opportunistic social-aware fashion. The model is then used to characterize how the expected delay experienced by messages varies with the different social structures in the network of the users.

Keywords: opportunistic networks, forwarding protocols, social-awareness, analytical model

1 Introduction

In the broad area of wireless multi-hop networking, Delay Tolerant Networks (DTNs) have recently stood out because of their ability to enable communications even when protocols designed for traditional Mobile Ad Hoc Networks (MANET) cannot do so. In fact, the main requirement of MANET protocols, i.e., the presence of an end-to-end path connecting the source and the destination of a message, can be rarely satisfied in networks, e.g., made up of subnetworks connected only by satellite links [4], or where the nodes are people moving around with their hand-held devices [17]. The latter case is the scenario considered in this paper. In order to distinguish the different applications of the delay tolerant paradigm, such networks have been named Pocket Switched Networks (PNSs) or opportunistic networks, because they opportunistically exploit contacts between users.

Messages in PSNs are routed along a multi-hop path across the nodes of the network. Being PSNs so unstable, source routing is inapplicable as the route
chosen by the source of the message is likely to change within a short time. For this reason, forwarding decisions in opportunistic networks are made hop by hop. The key problem of message forwarding in PSNs is thus the selection of the node to which the message (or a copy of the message, in the case of multi-copy schemes) should be handed over. First and simplest implementations of this new communication paradigm involved a large number of copies of the same message to be spread across the network, in order to maximize the probability that one of them will eventually arrive at the destination [22]. Smarter strategies have been developed later, with the aim of selecting only the best relays as next hops for each message. Social-aware strategies have proven [2, 11] to be very effective in forwarding messages in an opportunistic network. Their main idea is that while the connectivity graph of the network might be extremely unstable, the social graph, i.e., the network of relationships between users, is expected to vary on a much larger timescale than that typically of interest for the delivery of messages. This approach is indeed effective because of the correlation between sociality and mobility [18]: knowing social relationships between users enables us to estimate the likelihood of future encounters between nodes, which represents forwarding opportunities.

Despite being so popular as forwarding strategies, social-aware schemes are typically difficult to model analytically. The main contribution of this paper lies in the definition of an analytical model for the evaluation of social-aware single-copy forwarding schemes. This model, based on Markov Chains, allows us to describe a way for computing significant quantities, such as the expected number of hops or the expected delay, that characterize the forwarding performance.

The paper is structured as follows. In Section 2 we review the state of the art on forwarding modelling for opportunistic networks. In Section 3 we describe our analytical model for social-oblivious and social-aware forwarding. In Section 4 we use the above model for evaluating the performance of four reference forwarding strategies with different underlying social structures for the network of the users. Finally, in Section 5 we conclude the paper.

2 Related Work

As anticipated in the previous section, forwarding protocols can be classified, according to the type of information that they exploit when making forwarding decisions, into social-oblivious and social-aware protocols. Social-oblivious protocols do not use all information on the way nodes meet or relate with each other. This is the case of the Epidemic protocol [22], whose strategy is to generate and hand over a new copy of the message to each node encountered, and of the Direct Transmission protocol [9], in which messages can only be delivered to the destination when encountered directly. Their performance is typically poor because either they consume a lot of resources and overload the network (Epidemic) or they are not able to find a path to the destination even when many are available (Direct Transmission). For this reason, they are typically used as a baseline for performance evaluation.
Social-aware protocols, instead, exploit the social structure of the network of users in order to make forwarding decisions. This is because social-awareness enables the prediction of user encounters, which constitute forwarding opportunities. Some social-aware schemes focus only on encounters between nodes. This is the case of PROPHET [13], where the delivery probability of a node for a given destination is estimated based on previous encounters between nodes. Another approach is based on the exploitation of the roles of the nodes in the social graph associated with the network of users. Their main idea is that nodes that are more central in the social graph are likely to be better forwarders than the other nodes. Bubble Rap [11] and SimBet [5] belong to this category. Social context-aware protocols keep track of a variety of information on the environment – context – the users live in (e.g., the people they meet, the friends they have, the places they visit). Context information is then used to quantify the ability of nodes to deliver messages. HiBOp [2] pertains to this group.

As far as modelling is concerned, quite a few frameworks have been proposed for social-oblivious forwarding schemes [23, 10, 8, 19, 20]. Epidemic models, Markov Chains and random walk on graph are the mathematical tools used to model important metrics such as the expected delay. The problem with these models is that they all consider homogeneous networks, i.e., networks where node movements are independent and identically distributed. This is not the case of real networks made up from human users moving with their portable devices: some users may cluster and move together, others may never get in touch with each other. Such heterogeneity has been so far considered only in [21]. However, authors of [21] focus on multi-copy schemes, while in the following we consider single-copy schemes, i.e., schemes in which there is at any time just one copy of the message to be delivered.

3 A semi-Markov Model for Message Forwarding

In this section we model the forwarding process as a semi-Markov process, and then we perform a transient study in order to compute the expected number of hops and the expected delay experienced by messages. We start with a general framework, which we then specialize for four forwarding protocols representative of different approaches to forwarding. Let us first introduce in the next section the network model that we consider.

3.1 Network Model

Our model considers a network with $N$ nodes, moving around and meeting with each other. During contacts, nodes can exchange messages. For the sake of simplicity, we hereafter assume that messages can be exchanged only at the beginning of a contact between a pair of nodes (i.e., no periodic probing for new messages to relay during long contact periods), and that the transmission of the relayed messages can be always completed within the duration of a contact. The latter assumption is also justified by the fact that given the high dynamics of
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In opportunistic networks, the file size is expected to be small [15]. In addition, we assume that each message is a bundle [6], an atomic unit that cannot be fragmented. We also assume infinite buffer space on nodes. Given that we are considering single-copy schemes, buffer size is not expected to be critical, at least from low to medium network load. All the above assumptions allow us to isolate, and thus focus on, the effects of node mobility from other effects.

Given that messages are handed over from node to node before reaching their destination, the way nodes move heavily affects the delay experienced by messages. As for the mobility, the main role in the experienced delay is played by the inter-meeting time, which is defined as the time between two consecutive meetings between the same pair of nodes. In this paper we assume that such inter-meeting times can be described with an exponential distribution. Characteristic mobility times have been shown to follow an exponential distribution at least in their tail [12] [7]. Trading accuracy for tractability, here we assume the exponential property for the entire distribution. As a future work, we plan to relax the exponential assumption. In the following we denote as \( \lambda_{ij} \) the rate of the exponential distribution describing the process of encounters between two nodes \( i \) and \( j \).

3.2 Reference Forwarding Strategies

We abstract the variety of protocols described in Section 2 into the two main categories of social-oblivious and social-aware forwarding protocols. For these categories, we consider the following policies, which identify important traits of existing forwarding strategies. More specifically, among the social-oblivious schemes we consider the following.

**Definition 1 (Direct Transmission).** The source nodes can only deliver the message to the destination itself.

**Definition 2 (Always Forward).** The source node hands over the message to the first node encountered, and so does each intermediate node. The process stops when the message is delivered to the destination.

As for the social-aware schemes, a message (be it on the source node or on an intermediate relay) is handed over to another node only if the latter has a higher probability (we call it fitness) of bringing the message closer to its destination than the node currently holding the message. Based on how the fitness is computed, we define the following two policies.

**Definition 3 (Direct Acquaintance).** The source and each intermediate relay hand over the message to the first encounter having a higher fitness, where the fitness \( F^{D\Delta} \) is defined as the frequency of a direct meeting with the destination (Equation 1).

\[ F^{D\Delta} = \text{frequency of direct meeting with the destination} \]

3 Fragmentation can indeed add additional delay at the destination or, even worse, impair communication at all when some fragments are lost, due to the high round trip time of opportunistic networks.
\[ F_{i,d}^{DA} = \lambda_{i,d}, \forall i \neq d \]  

**Definition 4 (Social Forwarding).** Messages are delivered through a path with positive gradient of fitness, where the fitness \( F_{i,d}^{SF} \) of node \( i \) for a message addressed to node \( d \) is computed (Equation 2) as the weighted sum of the fitness for a direct acquaintance (\( F_{i,d}^{DA} \)) and the fitness for an indirect meeting (\( F_{i,d}^{I} \)).

\[ F_{i,d}^{SF} = \alpha F_{i,d}^{DA} + (1 - \alpha) F_{i,d}^{I}, \text{ where } 0 < \alpha < 1 \]  

Component \( F_{i,d}^{DA} \) is defined as in Equation 1. The second component is a measure of the likelihood of encountering a node that has high delivery probability and it is defined according to the following:

\[ F_{i,d}^{I} = f(F_{j,d}^{DA}) \quad \forall j \mid \lambda_{ij} \neq 0, j \neq d. \]  

There is a variety of possible choices for function \( f \) in Equation 3. Without loss of generality, in the rest of the paper we use \( f \equiv \max(\cdot) \).

Differently from the Direct Acquaintance policy, the Social Forwarding strategy is able to detect not only direct meetings with the destination, but also meetings with people that have a high probability of delivering the message to the destination. This strategy enables the exploitation of the delivery skills that are present in the environment surrounding the users, and not only of those of the user itself. In Section 4.4 we will show how important can be this exploitation.

### 3.3 The Forwarding Process as a Semi-Markov Process

A semi-Markov process is one that changes states in accordance with a Markov chain (called *embedded* or *jump* chain) but where transitions between states can take a random amount of time\(^{16}\). As such, it is fully described by the transition matrix associated with its embedded chain and by \( T_{i}^{exit} \), \( \forall i = 0, \ldots, n \), where \( T_{i}^{exit} \) denotes the distribution of time that the semi-Markov process spends in state \( i \) before making a transition.

We express our semi-Markov process in terms of the embedded Markov chain in Figure 1. Assuming that node \( i \) is currently holding a message whose destination\(^2\) is \( d \), the probability \( p_{ij}^{d} \) that node \( i \) will delegate the forwarding of the

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\(^2\) The chain is different for different destinations, because the convenient relays are generally not the same. However, for the sake of readability, in the following we drop superscript \( d \).
message to another node \( j \) is a function of both the likelihood of meeting node \( j \) and the probability that node \( i \) will hand over the message to node \( j \) according to the forwarding policy in use.

Theorem 1 proves that, under the exponential assumption for inter-meeting times (see Section 3.1), the semi-Markov process that describes the forwarding evolution becomes a Continuous Time Markov process, in which \( T_{\text{exit}}^i \) follows an exponential distribution.

**Theorem 1 (Exit time).** \( T_{\text{exit}}^i \), the time before the semi-Markov process exits state \( i \), follows an exponential distribution with rate \( \sum_{j=1}^{N} \lambda_{ij} p_{ij}^{\text{forw}} \), where \( p_{ij}^{\text{forw}} \) represents the probability that node \( i \) hands over the message to node \( j \) according to the forwarding scheme in use. \( T_{\text{exit}}^i \)'s expected value is thus given by the following:

\[
E[T_{\text{exit}}^i] = \frac{1}{\sum_{j=1}^{N} \lambda_{ij} p_{ij}^{\text{forw}}} \tag{4}
\]

**Proof.** See Appendix. \( \square \)

Below we derive the transition probabilities associated with the embedded chain in Figure 1 for each of the forwarding schemes described in Section 3.2.

**Proposition 1 (General form of the transition matrix for the forwarding process).** The transition matrix associated with the process of forwarding a message from a source node \( i \) to the destination node \( d \) is given in Equation 5, where, as an example, \( d = N \).

\[
P = \begin{pmatrix}
0 & p_{12} & \cdots & p_{1,N-1} & p_{1,N} \\
p_{21} & 0 & \cdots & p_{2,N-1} & p_{2,N} \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
0 & 0 & \cdots & 0 & 1
\end{pmatrix} \tag{5}
\]

The state associated with the destination node \( d \) is absorbing, because in state \( d \) the forwarding process is completed.

**Theorem 2 (Transition probabilities \( p_{ij} \)).** Probabilities \( p_{ij} \) in Equation 5 are given by:

\[
p_{ij} = \frac{\lambda_{ij} p_{ij}^{\text{forw}}}{\sum_{z} \lambda_{iz} p_{iz}^{\text{forw}}}, \tag{6}
\]

where \( \lambda_{ij} \) denotes the rate of encounters between node \( i \) and node \( j \), and \( p_{ij}^{\text{forw}} \) represents the probability that node \( i \) hands over the message to node \( j \) according to the forwarding scheme in use.

**Proof.** See Appendix. \( \square \)
In the following we derive $p_{ij}^{forw}$ for each of the reference forwarding policies in Section 3.2.

**Lemma 1 ($p_{ij}^{forw}$ for Direct Transmission).** The probability $p_{ij}^{forw}$ that node $i$ hands over the message to node $j$ when the Direct Transmission policy is in use is given by the following:

$$p_{ij}^{forw} = \begin{cases} 1 & j = D \\ 0 & \text{otherwise} \end{cases}$$

*Proof.* See Appendix.

**Lemma 2 ($p_{ij}^{forw}$ for Always Forward).** The probability $p_{ij}^{forw}$ that node $i$ hands over the message to node $j$ when the Always Forward policy is in use is given by the following:

$$p_{ij}^{forw} = 1, \quad \forall i, j$$

*Proof.* See Appendix.

**Lemma 3 ($p_{ij}^{forw}$ for Direct Acquaintance and Social Forwarding).** Under the Direct Acquaintance strategy, the probability $p_{ij}^{forw}$ that node $i$ hands over the message to node $j$ can be computed as:

$$p_{ij}^{forw} = \begin{cases} 1 & F_{i,j}^{DA} < F_{j,d}^{DA} \\ 0 & \text{otherwise} \end{cases}$$

Analogously, for the Social Forwarding scheme we have for $p_{ij}^{forw}$:

$$p_{ij}^{forw} = \begin{cases} 1 & F_{i,j}^{SF} < F_{j,d}^{SF} \\ 0 & \text{otherwise} \end{cases}$$

*Proof.* See Appendix.

Theorems 1 and 2 completely define the forwarding Markov process. Thus, we can exploit well known algorithms for Markov chain transient analysis in order to compute significant properties of the forwarding process. In the following, we describe how to compute the expected delay and the expected number of hops travelled by messages.

**Theorem 3 (Expected delay).** The expected delay $E[D_i^d]$ for a message generated by node $i$ and addressed to node $d$ can be obtained from the minimal non-negative solution to the following system:

$$\begin{cases} E[D_i^d] = 0 & i = d \\ E[D_i^d] = E[T_{exit}^i] + \sum_{j \neq d} p_{ij} E[D_j^d] & \forall i \neq d \end{cases}$$

*Proof.* See Appendix.
Theorem 4 (Expected number of hops). The expected number of hops $E[H^d_i]$ travelled by a message generated by node $i$ and addressed to node $d$ can be obtained from the minimal non-negative solution to the following system:

$$
\begin{align*}
E[H^d_i] &= 0 & i = d \\
E[H^d_i] &= 1 + \sum_{j \neq d} p_{ij} E[H^d_j] & \forall i \neq d
\end{align*}
$$

(12)

Proof. See Appendix.

□

4 Performance evaluation of social-aware forwarding

In this section we provide a detailed analysis of the performance of the Direct Transmission, Always Forward, Direct Acquaintance, and Social Forwarding schemes using the analytical model that we have described above. Under the assumptions in Section 3.1, this model is exact (for a comparison between analytical and simulation results please refer to [3]).

In the following we consider 15 nodes, which move around in the network and exchange messages according to the policies defined in Section 3.2. We assume that node movements are triggered by their social relationships with the other nodes of the network. Each scenario we consider is characterized by a different social structure connecting the nodes of the network. Based on this structure, we define node mobility according to the following algorithm. We assume that the default meeting rate is $\lambda$ for each pair of nodes connected by a social link. For those scenarios in which nodes are grouped into communities, however, assuming the user is in touch with $n$ communities, the rate of contact with users in each of those communities is $\lambda/n$.

Solving the systems in Theorems 3 and 4 provides us with a $N \times N$ matrix for the expected delay and a $N \times N$ matrix for the expected number of hops. Thus, the entry at position $(i, j)$ in the matrix gives the expected delay (number of hops) value for the $i - j$ node pair. For ease of visualization, we use a histogram of the expected delay and of the expected number of hops computed for the $N(N-1)$ pairs of interests. The bin width is set to 2 for the histograms of the expected delay and to 1 for the expected number of hops. Finally, please note that, in all the cases analyzed below, the resulting expected delay between any pair of nodes is a function of $\lambda$. In order to be able to plot such results we set $\lambda$ to 1. This choice has absolutely no effect on our performance comparison, because $\lambda$ appears only as a multiplying factor.

4.1 Model Validation

Before proving an extensive analysis for the forwarding performance of our references schemes, here we validate the analytical model proposed in Section 3 by means of simulations. To this aim, we developed a custom event-driven simulator, written in C++, which implements the forwarding strategies defined in Section 3.2. Simulation results are averaged over 100 independent replicas, and
95% confidence intervals are used. We show the results obtained considering a connected network of 15 nodes, divided into three communities. These communities are connected by a subset of nodes moving back and forth from one community to the other. These settings are analogous to those used in Section 4.3, to which we refer the reader for more details.

Figure 2 compares the probability density (estimated with the Kernel density estimation method) of the expected delay under the Direct Acquaintance policy for all possible node pairs and for both simulation and analysis. The match between model and simulations is very accurate. The same accuracy holds true for the other policies and settings. Here we omit the corresponding figures for space reasons.

4.2 Homogeneous network

Let us start our performance evaluation with the case of a complete social graph, i.e., a graph in which an edge connecting any pair of nodes exists. With this configuration all nodes are homogeneous from a mobility standpoint, i.e., every pair of nodes meets at the same rate $\lambda$. As a consequence, the concept of community does not apply here.

From Theorem 3, we obtain that the expected delay experienced by messages is the same for all the four policies and equal to $\frac{1}{\lambda}$. This result is not surprising, since all nodes are equivalent in this configuration, and choosing the one or the other does not make any difference. However, the different forwarding strategies may drastically differ in the number of hops needed to bring the message to its destination. Indeed, Figure 3 shows that the Direct Transmission, Direct Acquaintance, and Social schemes are all able to detect the fact that, as all nodes are equally good as relays, the most convenient strategy is to appoint the source of the message as its unique forwarder. Instead, the Always Forward
scheme, which continuously delegates the forwarding of the message to any new encounter, needs much more relays (from which the high number of hops), which in turn imply many (unneeded) transmissions, with the consequence of poor resource utilization.

![Fig. 3. Expected number of hops within an homogeneous network](image)

This homogeneous scenario is the one commonly used to evaluate the Epidemic forwarding strategy [22], which under ideal conditions (i.e., infinite bandwidth, infinite buffer space on devices, infinite battery lifetime, no contention, etc.) is the optimal forward policy as far as the expected delay is concerned. Being a multi-copy strategy, the Epidemic protocol does not fit into our model. However, we can exploit results presented in [23] in order to compare our single-copy strategies with Epidemic routing. The expected delay \( E[D_{\text{Epi}}] \) under Epidemic routing converges to \( \frac{\ln N}{N-1} \) as \( N \to \infty \). This value is thus generally much smaller than \( \frac{1}{N-1} \), and it decreases as \( N \) increases. However, the price to pay for this quick delivery is in terms of the number of copies disseminated into the network. According to [23], the expected number of copies \( E[C_{\text{Epi}}] \) injected into the network by Epidemic routing is \( \frac{N-1}{2} \). As \( N \) increases, \( E[C_{\text{Epi}}] \) also increases, thus flooding the network with many copies of the same data. When ideal conditions assumption is released, this will drastically affect the performance of Epidemic routing, and the delay provided will be much smaller than the optimal value, as shown in [1].
4.3 Connected communities: travellers distributed across each community

While in the homogeneous case all nodes were equal as far as their meetings were concerned, here we consider the case of a heterogeneous network. We equally distribute our 15 nodes into 3 communities. Each community is a complete subgraph, meaning that all nodes within each community are connected with each other. We also add links between communities in the social graph. These links are edges connecting a node in one community to another node in another community, until each community is connected with all the others. Due to the relation between social links and mobility, community $C_1$ will have two nodes (hereafter called *travellers*) visiting communities $C_2$ and $C_3$: specifically, one traveller goes to $C_2$ and back, the other goes to $C_3$ and back. The travellers in $C_2$ and $C_3$ have an analogous behavior.

Figure 4 shows the forwarding performances as far as delay is concerned. The Direct Transmission scheme suffers when the source and the destination of the message do not get in touch with each other directly, thus producing in this case infinite delays. This is because with Direct Transmission nodes can only deliver their messages directly to the destination, thus missing all the opportunities offered by relaying; when the destination is never met, the message cannot be delivered. Instead, Direct Acquaintance, Social, and Always Forward are able to exploit the social bridges between communities and to hand over the message to the convenient node. As before, however, the Always Forward approach is totally at random, and many hops may be required before the message eventually finds, by chance, its destination (Figure 5). Social strategies are instead able to choose only the *best* relays, thus limiting the number of hops and resource consumption.

![Fig. 4. Expected delay with connected communities (Sec. 4.3)](image-url)
In this section we use the same scenario as in Section 4.3, except that we assign travellers only to community $C_1$. As in the previous case, the network is connected (i.e., it exists at least one multi-hop path between every pair of nodes). The difference is that, while in Section 4.3 all communities had a direct link through the travellers, here $C_2$ and $C_3$ cannot communicate directly, and they have to exploit the forwarding capabilities of the visiting travellers from $C_1$.

Figure 6 shows the expected delay experienced by messages in this scenario. Both the Direct Acquaintance and the Direct Transmission scheme are not able to deliver a subset of messages. In the case of the Direct Transmission scheme the reason lies in the absence of direct contact between the source of a message and its destination. In the case of the Direct Acquaintance policy, this behaviour follows directly from the definition of the forwarding strategy. In fact, with Direct Acquaintance a node hands over a message to a node that has a higher probability of meeting the destination, measured in terms of direct encounters (Equation 1). The traveler that visits $C_1$ does not meet any nodes of $C_3$ directly, thus it is not considered a good relay by the Direct Acquaintance scheme. A more efficient strategy should also consider the transitivity of opportunities (e.g., node $a$ meets $b$, which in turn meets $c$, thus $a$ can be considered good relay for destination $c$). This transitivity of encounters is detected by the Social Forwarding strategy, which indeed is able to deliver all messages to their destinations. The Always Forward strategy is, as before, able to deliver all messages, but using many relays (Figure 7), even more than in previous scenarios. The reason is that, being the forwarding opportunities so limited, with the Always
Forward strategy the destination is typically found by chance after many (bad) relays have been used.

![Graphs showing expected delay with connected communities](image)

Fig. 6. Expected delay with connected communities (Sec. 4.4)

5 Conclusions

In this paper we have proposed an analytical model based on Markov processes for social-aware forwarding in opportunistic networks. Using this model, we have discussed how to compute the expected delay and the expected number of hops of messages delivered according to four reference forwarding scheme, of which two are able to exploit social information when making forwarding decisions. In the second part of the paper, we have used the model to compare the forwarding performance of social-oblivious and social-aware strategies in terms of expected delay and expected number of hops. In general, social-aware policies turn out to provide lower delays while at the same time keeping the number of hops down, thus improving the efficiency of the network. We have also shown how the ability of exploiting indirect connections between nodes may be a key strategy when forwarding opportunities are limited, and for this reason we have identified the Social Forward strategy as the most promising social-aware approach.

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Fig. 7. Expected number of hops with connected communities (Sec. 4.4)

References

Appendix

Proof. (Theorem 1) The time $T_{i}^{exit}$ before the forwarding Markov chain exits state $i$ can be computed as the time before node $i$ hands over the message to any of the potential relays for destination node $d$.

First, let us compute the distribution of the time before node $i$ hands over a message to another node $j$. The first condition for this to happen is that node $i$ and node $j$ meet. Meetings between node $i$ and node $j$ occur with a rate $\lambda_{ij}$. Then, each of these meetings is exploited for a message exchange by the forwarding protocol with probability $p_{ij}^{forw}$. This implies that the time $T_{forw}^{ij}$ between two consecutive message exchanges is obtained as the sum of $n$ exponential random variables with rate $\lambda_{ij}$, where $n-1$ is the number of meetings between node $i$ and node $j$ not exploited by the forwarding algorithm.

From standard probability theory [16] we know that the sum of $n$ exponential
random variables having the same rate $\lambda_{ij}$ follows an Erlang distribution with shape $n$ and rate $\lambda_{ij}$. The probability of having exactly $n-1$ meetings before the first message exchange is given by a geometric distribution with success probability $p = p_{ij}^{\text{forw}}$. Thus, the probability density function of $T_{ij}^{\text{forw}}$ can be written as:

$$T_{ij}^{\text{forw}}(x) = \sum_{n=0}^{\infty} (1 - p_{ij}^{\text{forw}})^{n-1} p_{ij}^{\text{forw}} \frac{\lambda_{ij}^n x^{n-1} e^{-\lambda_{ij} x}}{(n-1)!}$$

Equation 13 converges to:

$$T_{ij}^{\text{forw}}(x) = \lambda_{ij} p_{ij}^{\text{forw}} e^{-\lambda_{ij} p_{ij}^{\text{forw}} x}$$

Thus, $T_{ij}^{\text{forw}}$ follows an exponential distribution with rate $\lambda_{ij} p_{ij}^{\text{forw}}$, for all $i \neq j$.

We are interested in the event of node $i$ handing over a message to any node $j$. Thus, the time $T_i^{\text{exit}}$ before the first forwarding event at node $i$ is thus given by $T_i^{\text{exit}} = \min_{j \neq i} \text{Exp} \left( \lambda_{ij} p_{ij}^{\text{forw}} \right)$. The random variable resulting from the minimum of a set of exponential random variables follows an exponential distribution with rate equal to the sum of the rates of the single random variables [16]. Thus, here we have the following:

$$T_i^{\text{exit}} = \text{Exp} \left( \sum_{j=1}^{N} \lambda_{ij} p_{ij}^{\text{forw}} \right)$$

Then, from standard probability theory [16], Equation 4 follows directly. \(\square\)

**Proof. (Theorem 2)** The chain in Figure 1 goes from state $i$ to state $j$ only when node $i$ hands over a message to node $j$. The probability that the chain will go from state $i$ to state $j$ instead of moving to any other state $z$ is given by the probability that the exchange with $j$ is “the first to arrive”. From Equation 14, we know that the random variable related to $j$’s forwarding exchange rate with $i$ is $T_{ij}^{\text{forw}} = \text{Exp}(\lambda_{ij} p_{ij}^{\text{forw}})$, the one associated with $i$ and any other node (except $j$) is $T_{i-\text{others}}^{\text{forw}} = \min_{z \neq i,j} \left\{ T_{iz}^{\text{forw}} \right\} = \text{Exp} \left( \sum_{z \neq i,j}^{N} \lambda_{iz} p_{iz}^{\text{forw}} \right)$. From standard probability theory [16] follows that node $j$ is the first to arrive with a probability equal to $P(T_{ij}^{\text{forw}} < T_{i-\text{others}}^{\text{forw}}) = \frac{\lambda_{ij} p_{ij}^{\text{forw}}}{\sum_{z \neq i,j}^{N} \lambda_{iz} p_{iz}^{\text{forw}}}$. \(\square\)

**Proof. (Lemma 1)** It follows directly from the definition of the forwarding strategy, because the source node can only hand over the message to the destination node. \(\square\)

**Proof. (Lemma 2)** According to the Always Forward scheme, the forwarding is always delegated to the first node encountered, thus Equation 8 follows. \(\square\)
Proof. (Lemma 3) Under the two social-aware schemes, messages follow a positive gradient of delivery probability, which is measured in terms of the fitness of nodes as relay. Thus, Equations 9 and 10 follow the definition of the two forwarding policies.

Proof. (Theorem 3) The expected delay from node $i$ to node $d$ is equivalent to the expected hitting time on $d$ from state $i$. As we recall from Markov process analysis [14], the expected hitting times $D_{i}^{d}$, i.e., the expected time needed to go from state $i$ to state $d$, are the minimal non-negative solutions to the system in Equation 11, where we use the result from Theorem 1 in order to account for the time needed to exit state $i$.

Proof. (Theorem 4) The expected number of hops travelled by a message is equivalent to the expected number of states visited in the embedded chain in Figure 1 before reaching $d$. This expected number of visited states before reaching $d$ is nothing but the expected hitting time for the embedded discrete Markov chain. Thus, the expected number of hops $E[H_{i}^{d}]$ is given [14] by the minimal non-negative solutions to the system in Equation 12, where 1 accounts for exiting state $i$. 

\[ \text{Proof. (Theorem 4)} \]