On the trade-off between delivery delay and power consumption in opportunistic scenarios

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***Abstract*—Opportunistic networking is rapidly emerging as a suitable communication paradigm to characterize social networking applications and contents dissemination. However, due to the sparsity of the opportunistic network, it is expected that the considered mobility model will play a crucial role in the delivery performance of the opportunistic system. Accordingly in this paper we present an analysis of the impact of different conventional mobility models on the delivery performance of opportunistic networks. In particular, we focus on the estimation of the packet delivery delay and the power consumption associated to the delivery procedure which are the two key metrics to be traded-off according to the application requirements.**

I. Introduction

In opportunistic networks nodes intermittently communicate with each other only when in closest proximity. Such a communication paradigm is suitable to characterize social interactions between users moving around and exchanging information without exploiting the telecommunication infrastructure that can be provided by the telco operators.

This opportunistic communication paradigm poses several challenging issues such as energy efficiency, optimal routing design and minimization of data delivery delay and losses.

Numerous studies showed that mobility can increase the performance of wireless data dissemination mechanisms [1], [2], [3] both in terms of capacity and network connectivity. In particular, in [3] it was shown that even considering very simple mobility models (e.g. random walk), but associated to dynamic variations in nodes speed, positive effects on the connectivity of the network can be observed.

Obviously mobility patterns are a relevant concern in mobile communications, especially in opportunistic networks, where it has been often proposed to consider static source nodes and add few mobile sinks to speed up the delivery process. For this reason, several research studies addressed the pattern optimization problem for the definition of the best trajectory for the mobile nodes so as to increase network efficiency and reduce delay and losses.

The use of mobile sinks in opportunistic networks has been proposed in the past literature on *Delay Tolerant Networks* (DTNs) that were designed for those scenarios in which, in principle, delivery delay and packet losses are not an issue [4]. Even if DTNs were theorized to support large delay in interplanetary communications, DTNs have been also proposed for terrestrial communications in order to support nodes mobility [4]. The use of mobile nodes in DTNs was theorized as the *Mobile Ferrying* (MF), a proactive mobility-assisted approach proposed for ad hoc network scenarios which utilizes a set of special mobile nodes, called message ferries, to provide communication services for nodes in the network. Similarly the DataMule concept [5] has been also proposed where mobile entities (called MULEs) pick up data from sensors when in close range, store it, and drop it to wired access points.

Inspired by these papers, in this work we present a study of the impact of different mobility schemes on packet delivery and power consumption in opportunistic scenarios. More in depth, we compare the performance achievable by using simple mobility approaches such as random waypoint, random mobility and Manhattan grid for the mobile sinks and figure out a trade-off between the reduction in power consumption and the prompt data delivery. We also investigate on the effect of partial knowledge of nodes' mobility pattern and see how this impacts on the same performance metrics.

The remainder of this paper is organized as follows. In Section II the addressed scenario is described. Section III is devoted to the discussion of the analytical framework. Performance results are presented in Section IV. Finally, the concluding remarks are given in Section V.

II. Scenario Overview

In this paper we address a network scenario where N sensor devices are deployed in the network area; a mobile sink then moves around and collects the data from the sensors upon coming in their proximity [6]. We assume that each sensor device is equipped with a wireless interface that allows to communicate with other nodes in the proximity, either static sensor devices or mobile sink(s). In this way multi-hop communications can be performed and nodes can choose if transmitting their data to the mobile sink upon/when coming into proximity or exploiting other sensor devices with which they can occasionally come into contact to deliver the data to the final destination. Moreover, due to the duty cycle implemented by sensor devices to save energy and increase network lifetime, nodes can be occasionally disconnected from the network. Accordingly, in order to perform multi-hop communications we assume that nodes execute neighbor discovery protocols to identify the network topology [7].

To deliver the data into the network, each node is able to identify the next hop neighbor which is closer to the mobile sink at each time instant. Hence, each sensor node is able to decide either to wait until the mobile sink will be in its proximity or to forward data to its next hop neighbor by evaluating and comparing the expected delay and power consumption in both cases so as to maximize its achievable throughput. Use of such a geographic forwarding not only reduces the transmission delay to the mobile sink, but also allows to decrease the power consumption. In fact, tuning of the transmission power can be done so that the sensor device can try to use less power to transmit to closer neighbors or to the mobile sink. This is a desirable feature in energy and delay constrained opportunistic communications [8].

Furthermore, we assume that the delay introduced by multi-hop forwarding is negligible if compared to the time needed for the mobile sink to come close enough to the sensor node.

Identification of the closest neighbor node towards the mobile sink requires knowledge of the trajectory of the mobile sink, which strictly depends on the mobility pattern used by the mobile sink. To this purpose, two different scenarios can be considered:

- *Complete Mobility Information* (CMI): in this case we assume that each sensor node knows exactly the mobility pattern of the mobile sink. Thus, each sensor is aware of the current and future positions of the mobile sink. CMI can be obtained when the mobile sink moves according to a periodic trajectory [6] or a network infrastructure is used to continuously provide the mobile sink trajectory coordinates to the deployed sensors. Observe that the CMI represents an ideal benchmark for the system because it would imply a huge overhead which in real systems is usually avoided.
- *Incomplete Mobility Information* (IMI): nodes have only partial knowledge of the position of the mobile sink, e.g. sensors are aware of the next T movements of the mobile sink; thus, the trajectory of the sink is not completely known but only a time window T of the past and future mobile sink positions is known.

In case the IMI model is assumed, two conditions will be distinguished depending on if the trajectory will be perfectly known during the time window T or if it will be known only probabilistically according to a prediction mechanism. More specifically we will distinguish between:

- *Short Time Guaranteed Knowledge* (STGK): each sensor node is aware of the mobile sink movements in the next time window of length T. The larger is T, the larger is the knowledge of the future trajectory of the sink. Obviously, when $T \to \infty$ each sensor will exactly know the position of the sink at each time instant, so the IMI scenario becomes a CMI one.
- *Short Time Prediction Knowledge* (STPK): each sensor node knows only probabilistically the position of the mobile sink among a set of M possible predicted trajectories. The j-th trajectory $\mathbf{t}_j$ will be described according to a probability p_j representing the probability that the trajectory $\mathbf{t}_j$ is the one selected by the mobile sink. The position of the sink at time t, $\theta(t)$, will be described through a discrete pdf where $\theta(t)$ takes values in the interval $[\theta_1(t), \theta_2(t), ..., \theta_M(t)]$ and $\theta_j(t)$ represents the position of the mobile sink if moving along the j-th trajectory $\mathbf{t}_j$ at the $t \in 1, 2, ..., M$.

III. Analytical Framework

In this section we introduce an analytical framework which models the delivery process to the mobile sink. The framework aims at the evaluation of a trade-off between delay and power efficiency in delay tolerant applications when one or more mobile sinks opportunistically collect the data at the sensor devices during their movement. To this purpose, while the mobile sink moves around according to its trajectory, a sensor node may decide if exploiting the sink availability so holding the packet it wants to send until the sink becomes closer and so decreasing power consumption or not. Alternatively, the sensor node can in fact decide to start forwarding the data packet to its neighbors so that the mobile sink can be intercepted for relaying before reaching the minimum distance from the original packet source.

This is clearly a trade-off problem and, thus, an analytical framework which allows to calculate the expected delivery cost, given a threshold on the maximum tolerable delay, Δ_M, is required.

Accordingly, in Section III-A we characterize the system and introduce some notation; then, in Section III-B, we evaluate the expected delivery cost as a function of the threshold on the maximum tolerable delivery delay, Δ_M.

A. System Model

Assume that N nodes and one mobile sink are deployed in a given sensed area. An appropriate reference system can be introduced which allows to express any possible location within the sensed area through a pair (x, y). Accordingly, at any time instant, t, the position of the generic i-th sensor node can be represented by a *position vector*

$$\overrightarrow{p}_i(t) = (x_i(t), y_i(t)) \quad \text{with } i \in [0, N] \tag{1}$$

where $(x_i(t), y_i(t))$ represent the coordinates of node i at time t. For simplicity, in the following, we will use $i = 0$ to indicate the mobile sink.

According to this reference system, the distance between two nodes i and j at time t, $d_{i,j}(t)$, can be calculated as follows:

$$\begin{aligned} d_{i,j}(t) &= \|\overrightarrow{p}_i(t) - \overrightarrow{p}_j(t)\| = \\ &= \sqrt{[x_i(t) - x_j(t)]^2 + [y_i(t) - y_j(t)]^2} \quad \forall i, j \in [0, N] \end{aligned} \tag{2}$$

We assume that all nodes, except for the mobile sink, are stationary, i.e.,

$$\overrightarrow{p}_i(t) = \overrightarrow{p}_i = (x_i, y_i) \quad i \in [1, N] \text{ and } t \geq 0 \tag{3}$$

Moreover, we assume that each node knows its own position as well as the mobile sink position. To this purpose, GPS or GPS-less techniques [9] can be exploited. Assuming that the mobile sink moves around the sensed area and nodes know its trajectory, for any time instant t, any node, i, can evaluate its distance from the sink, $d_{i,0}(t)$.

For any couple of time instants t_1 and t_2, with $t_1 < t_2$, we denote as $d_i^{\min}(t_1, t_2)$ the minimum distance between the node i and the mobile sink in the time interval $[t_1, t_2]$, i.e.,

$$d_i^{\min}(t_1, t_2) = \min_{t_1 \leq t \leq t_2} \{d_{i,0}(t)\} \tag{4}$$

and as $\tau_i^{\min}(t_1, t_2)$ the time instant when the minimum distance is reached for the first time in $[t_1, t_2]$, i.e.,

$$\begin{array}{l} \tau_i^{\min}(t_1, t_2) = \{t^* : d_{i,0}(t^*) < d_{i,0}(t), \forall t \in [t_1, t^*[\text{ and} \\ d_{i,0}(t^*) \leq d_{i,0}(t), \forall t \in [t^*, t_2]\} \end{array} \tag{5}$$

Suppose that at time $t = 0$ a given node i receives from the application a new data packet which must be delivered to the mobile sink and that, according to the application requirements, the information must reach the sink within a time interval Δ_M. It is obvious that the node can save power by storing the packet in a local buffer until time $\tau_i^{\min}(0, \Delta_M)$, and routing the packet towards the point characterized by the position vector $\overrightarrow{p}_0\left(\tau_i^{\min}(0, \Delta_M)\right)$. In the following we will calculate the delivery cost associated to this procedure.

B. Delivery cost

Let us denote $C(d)$ the expected cost in terms of power consumption required to route an information packet between two points S and D whose distance is d. According to what was discussed in the previous section, the delivery cost we must evaluate is $C\left(d_s^{\min}(0, \Delta_M)\right)$.

In this section we calculate this cost function $C(d)$ as follows:

$$C(d) = \begin{cases} P + C(d - \overline{G(d)}) & d > R \\ P & d \leq R \end{cases} \tag{6}$$

where

- P is the power consumed to transmit and receive a single packet;
- R is the radio coverage of the current relay node, either the original packet source or the current packet relayer;
- $\overline{G(d)}$ is the *expected one-hop progress* towards the destination distant d. To better explain the concept of *progress* [13], let us provide an example. As showed in Figure 1 a certain node S has a packet to transmit towards the destination D whose distance from node S is d. Suppose that, in the radio coverage range of S, the more convenient next relay node (i.e. the node closer to D) to forward a packet towards D is node M, whose distance from the destination is d'. If this is the case, the *progress* towards the destination is given by $(d-d')$. Accordingly, $\overline{G(d)}$ is the expected value of $(d - d')$.

In the following we denote $G(d)$ the random variable representing the progress towards the destination achieved in *one hop* when the destination has a distance d from the current relay node, S. In [6] it is shown that $\overline{G(d)}$ can be computed

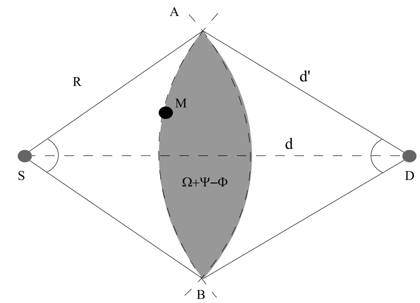

Fig. 1. Area where the next hop relayer must be found.

as follows:

$$E\{G(d)\} = \int_{-\infty}^{+\infty} x \cdot f_{G(d)}(x)dx = R - \int_0^R F_{G(d)}(x)dx \tag{7}$$

where

$$F_{G(d)}(x) = \begin{cases} 0 & x < 0 \\ e^{-\lambda \cdot a(d-x,d)} & 0 \leq x < R \\ 1 & x \geq R \end{cases} \tag{8}$$

and $a(r, d) = \Psi + \Omega - \Phi$, where Ψ, Ω and Φ are the areas shown in Figure 1.

IV. Performance evaluation

In this section we will estimate the network performance in IMI scenarios when different mobility patterns are employed. We identify three different mobility models: *Random Walk* (RW), *Random Waypoint* (RWP) and *Manhattan Grid* (MAN) [10] and assume to have only partial and imperfect information on the trajectory of the mobile sink. Then we also compare the achieved performance with the ideal one, i.e. the one achieved with CMI. We assume that the sink moves inside a constrained square area with a velocity $v \in [v_{min}, v_{max}]$, where v_{min} and v_{max} are respectively the minimum and maximum possible velocity.

According to the discussion carried out in Section II we identify two different settings of the parameters of the IMI scenario depending on the available information about sink's movements. More specifically we consider:

- *Short Time Guaranteed Knowledge* (STGK): each fixed node is aware of the next T movements of the mobile sink. The larger is T, the more extensive is the knowledge of the trajectory of the sink.
- *Short Time Prediction Knowledge* (STPK): each fixed node knows a set of M predicted possible trajectories each one characterized through a probability of being selected.

As discussed in the following, network delivery performance is strongly impacted by several key factors: *i)* mobility pattern; *ii)* knowledge of mobile sink movements; *iii)* node density in the area. Therefore, in Section IV-A we discuss network performance according to the above discussed network metrics.

A. Numerical Results

The simulation scenario consists of a square area of $400 \times 400\ m^2$ where N sensors are deployed according to a Poisson distribution and a mobile sink is moving to collect sensed data. Mobility traces are generated by Mobisim [11] which gives mobility traces for several mobility patterns and mobility parameters. In order to generate mobility traces for the MAN model we assume that a 3×3 Manhattan grid map is employed.

We also assume that the power needed to transmit a packet is $P = 4\mu W$ which is the power consumption of Crossbow MICAZ commercial sensor devices [12]. The sensors coverage radius is $R = 75m$.

Performance evaluation was performed through a Java simulator. Each simulation was executed 20 times so as to give results with a precision of 95%. The performance metrics being considered are:

- *Packet Delivery Ratio* (PDR), i.e. percentage of packets which are successfully delivered to the mobile sink among those generated into the network;
- *Packet Delivery Delay*, i.e. the time needed to generate a packet and to deliver it to the mobile sink. We assume that transmission, propagation and queueing delays are negligible if compared to the delay needed for the mobile sink to come into proximity of the sensor devices;
- *Delay Reduction* (Δ), i.e. the difference between the delivery delay δ_{nM} when no multi-hop communication is exploited (i.e. the sensor node waits until the mobile sink comes in its proximity) and the packet delay δ_M when the sensor node starts sending its data packet through multi-hopping to its neighbors so that the mobile sink trajectory is intercepted in advance. Thereby $\Delta = \delta_{nM} - \delta_M$;
- *Power Consumption*, i.e. the amount of power needed to transmit and receive a packet.

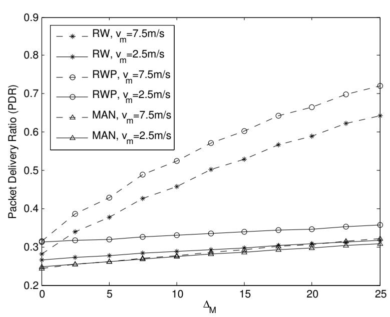

Fig. 2. Packet Delivery Ratio (PDR) for different values of the average velocity for the mobile sink as a function of Δ_M (STGK case).

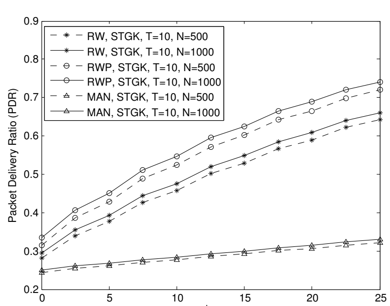

Fig. 3. Packet Delivery Ratio for different values of node density as a function of Δ_M (STGK case).

In Figure 2 we show the PDR as a function of the maximum tolerable delivery delay Δ_M and the average velocity (v_m) of the mobile sink in a STGK scenario with time window $T = 10$ s; this means that each sensor node knows exactly the positions of the sink for the following 10 seconds. Note that the PDR

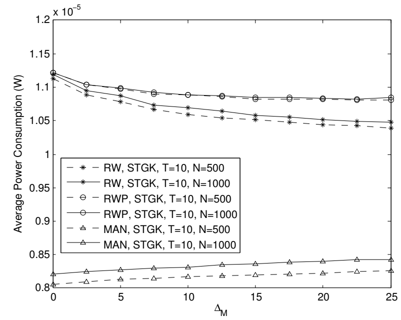

Fig. 4. Average Power Consumption for different values of node density as a function of Δ_M (STGK case).

increases as Δ_M and v_m increase. This is due to the fact that the larger is Δ_M, the larger is the time after which a packet becomes obsolete and is dropped. Therefore, when large delay is tolerable, a packet will be successfully delivered to the sink with higher probability. As expected the PDR increases for higher values of v_m as the sink moves faster and is able to cover the network area in less time. Figure 2 also shows that RWP and RW achieve better performance than MAN.

Figures 3 and 4 illustrate the PDR and the average power consumption when varying the number of nodes in the area as a function of Δ_M. Our simulations show that, as expected, the PDR is higher in high density scenarios as compared to low density ones. This is due to the decrease in the distance between pairs of nodes so that multi-hop relaying can be proficouously employed to let the packet reach the mobile sink before the mobile sink itself comes closer to the source node. Although in Figure 4 the power consumption decreases as Δ_M increases in case of RW and RWP, observe that the increase in PDR for high node density scenarios has a cost. In fact, the average power consumption for $N = 1000$ nodes is higher than in the case of $N = 500$ nodes for RW, while for RWP the power consumption remains basically the same. The higher power consumption for RW is due to the higher number of multi-hop relaying communications which cause a higher number of packet transmissions. In case of RWP instead, better performance can be obtained as compared to RW and MAN due to the larger coverage supported. In Figure 4 we also observe that for MAN, as soon as we increase the density, the power consumption rises up. This is because, due to the constraint on the mobile sink movement, a higher number of nodes does not help, in general, to reduce the power consumption needed to reach the sink. In Figure 5 the Delay Reduction Δ is illustrated upon varying the degree of knowledge of the mobile sink trajectory as well as the maximum tolerable delay Δ_M. As already observed above, the knowledge of the trajectory of the mobile sink is a big concern in opportunistic networks. In our simulation we show that the higher is the knowledge of the network (i.e. the higher T), the higher is the achievable efficiency of the network by exploiting

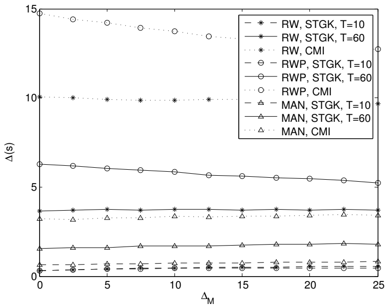

Fig. 5. Average Delay Reduction Δ as a function of Δ_M for different values of T, different mobility models and the IMI and CMI cases.

movements prediction and multi-hop communications in order to increase PDR and decrease packet delivery delay. In fact, as shown in Figure 5, a better knowledge of the mobile sink movements helps to reduce packet delay so that the Delay Reduction Δ increases with parameter T and reaches its maximum in CMI scenarios due to the perfect knowledge of the trajectory of the mobile sink. A comparison between

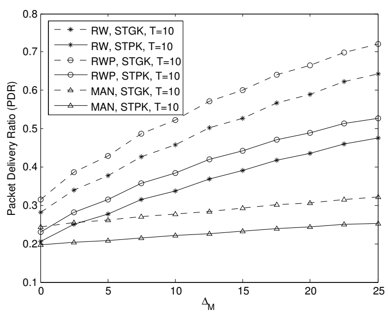

Fig. 6. Comparison of the Packet Delivery Ratio in STGK and STPK scenarios as a function of Δ_M for different mobility models.

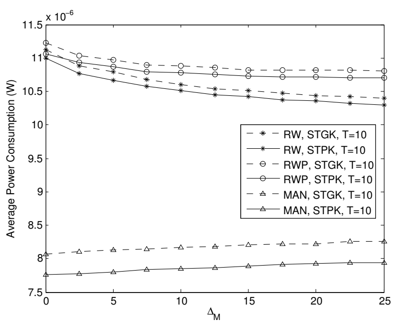

Fig. 7. Comparison of the Average Power Consumption in STGK and STPK scenarios as a function of Δ_M for different mobility models.

STGK and STPK scenarios is illustrated in Figures 6 and 7, where we show the PDR and the average power consumption as a function of Δ_M and T, respectively. More in detail we analyze the effect of uncertainty in the position of the mobile sink. In our simulation we assumed a preferred mobile sink trajectory $t_j^* \in \mathbf{t}_j$ with probability of being chosen equal to $p_j = 0.7$.

As shown in Figure 6, the PDR in the STPK case is always worse than in the STGK case; the latter in particular allows to improve performance of about 36% for the RW and RWP models, and less than 25% for the MAN model. In Figure 7, instead, we observe that the average power consumption is lower when there is uncertainty in the trajectory of the sink. Therefore, the uncertainty on the sink trajectory forces the nodes to forward a reduced number of packets by preferring a conservative behavior to reduce the power consumption.

V. Conclusion

In this paper we investigated on the impact of mobility uncertainty in sensor networks where sensed data generated by stationary sensor devices are opportunistically collected by a mobile sink moving throughout the area. We also evaluated the impact of the mobile sink mobility pattern on packet delivery ratio, power consumption and packet delay. A comparison of the achievable performance in case of both complete and incomplete knowledge of the mobile sink trajectory has been presented. The main result of this investigation is that we estimated how, upon increasing the degree of unpredictability in mobile sink trajectory, network performance decreases as nodes prefer to save their power instead of relaying sensed data. This egoistic ”saving” mechanism lies at the basis of the opportunistic networking paradigm.

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