Duty Cycling in Opportunistic Networks: the Effect on Intercontact Times

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1. INTRODUCTION

The widespread availability of smart, handheld devices like smartphones and tablet has stimulated the discussion and research about the possibility of extending the communication opportunities between users. Particularly appealing, towards this direction, is the opportunistic networking paradigm (both as a standalone solution and in synergy with the infrastructure in mobile data offloading scenarios [12]), in which messages arrive to their final destination through consecutive pairwise exchanges between users that are in radio contact with each other. Thus, user mobility, and especially user encounters, are the key enablers of opportunistic communications. Unfortunately, ad hoc communications tend to be very energy hungry [4] and no user will be willing to participate in an opportunistic network if they risk to see their battery drained in a few hours.

Energy issues in opportunistic networks have still to be fully addressed. In particular, there are very few contributions that study how power saving mechanisms impact on the amount of contacts that can be exploited to relay messages. With duty cycling, messages can be exchanged only when two nodes are in one-hop radio range and they’re both in the active state of the duty cycle. So, power saving effectively reduces forwarding opportunities, because contacts are missed when at least one of the devices is in a low-energy state that does not allow it to detect the contact. Since some contacts are missed, the measured intercontact times, defined as the time interval between two consecutive detected encounters between the same pair of nodes, is, in general, larger and this clearly affects the delay experienced by messages. So far, this aspect (i.e., the fact that duty cycling can affect the detected pairwise contacts) has been largely ignored in the literature, despite the fact that all popular off-the-shelf wireless technologies (e.g., WiFi, Bluetooth) already implement some sort of periodic contact probing.

The goal of this work is to understand how the exploitable mobility, i.e., the amount of contacts that can be used by node pairs for communicating, is modified by the duty cycling policy. To this aim, the contribution of this paper is twofold. First, we derive an analytical model of the measured intercontact times between nodes after duty cycling is factored in, i.e., by taking into account that some contacts may be missed. While deriving a closed-form characterisation of the detected intercontact times is in general too complex from an analytical standpoint, this model can be used to compute numerically their first two moments. As it is well-known, this is sufficient to approximate the distribution of the detected intercontact times using hyper- or hypo-exponential distributions, using standard techniques [9]. Thus, with this model, we are able to obtain an approximated representation of intercontact times measured when a duty cycling policy is in place under virtually any distribution.

The second contribution of the paper is the solution to the above model for the case of exponential intercontact times, which is a popular assumption in the related literature [6, 7] (even if a general consensus on which is the best distribution for representing realistic intercontact times has yet to be achieved). With exponential intercontact times, the proposed model can be solved approximately in closed form and, under a specific condition that we derive, the detected intercontact times are still exponential, but with a rate pro-
portional to the inverse of the duty cycle. This result tells us that models (e.g., of the delay [3, 7]) that assume exponential intercontact times (which are typically tractable and thus very popular in the literature) can still be used when a duty cycling policy is in place, since the original rates are scaled proportionally to the inverse of the duty cycle.

2. PROBLEM STATEMENT

We use duty cycling in a general sense here, meaning any power saving mechanism that hinders the possibility of a continuous scan of the devices in the neighbourhood. We assume that nodes alternate between the ON and OFF states. In the ON state, nodes are able to detect contacts with other devices. In the OFF state (which may correspond to a lower power state or simply to a state in which devices are switched off) contacts with other devices are missed. In this work we consider a duty cycling policy in which the duration of the ON and OFF states is fixed\(^1\) and we abstract from the specific wireless technology used for pairwise communications. We assume that the duty cycle process and the contact process are independent and, considering a tagged node pair, we denote with \(\tau\) the length of the time interval in which both nodes are ON, and with \(T\) the period of the duty cycle. Thus, \(T - \tau\) corresponds to the duration of the OFF interval and \(\Delta = \frac{T}{\tau}\) is the actual duty cycle (i.e., the percentage of time nodes are in the ON state). We specifically assume that ON and OFF intervals are coarsely synchronised across nodes, such that all nodes stay active only for a portion of time equal to \(\Delta\) while still having the opportunity to detect all the other nodes during ON intervals\(^2\). We assume that the ON interval can start anywhere within \(T\) and we denote its starting time with \(s_0\) (for convenience of notation, we count duty cycles starting from the first one in which a contact is detected). Then, \(s_1 = s_0 + \tau\) denotes the time instant at which the ON interval ends. Hence, ON intervals will be of type \([s_0 + iT, s_1 + iT]\), with \(i \geq 0\) and OFF intervals of type \([s_1 + iT, s_0 + (i + 1)T]\), with \(i \geq 0\). Focusing on a tagged node pair, we can represent how the duty cycle function evolves with time as in Equation 1:

\[
d(t) = \begin{cases} 
1 & \text{if } t \mod T \in [s_0, s_1) \\
0 & \text{otherwise}.
\end{cases}
\]

When \(d(t) = 1\), both nodes are ON, thus their contacts, if any, are detected. The opposite holds when \(d(t) = 0\). Basically, \(d(t)\) operates a bandpass filtering on the contact process between a pair of nodes.

Function \(d\) determines the way contacts are discovered. In the following, to make the analysis more tractable, we assume that a contact event is detected only if it starts during an ON period. This assumption is reasonable when the duration of a contact is much smaller than the duration of the OFF interval. In fact, in this case the probability of the contact lasting until the next ON interval is negligible. In real contact datasets (see, e.g., [5] or those considered in Section 3.2) the contact duration is in the order of tens of seconds for the majority of samples. In [5], for example, more than 50% of contact duration samples are smaller than 48s. Since Trifunovic et al. [10] have derived that, with Bluetooth and WiFi, scanning intervals greater than 100s perform significantly better energy-wise, the above assumption can be considered reasonable\(^3\).

We now focus on the contact process. Similarly to the related literature \([7, 3]\), we assume that, from the mobility standpoint, node pairs are independent and that the contact process of each pair can be described as a renewal process. We denote the time between the \((i - 1)\)-th and \(i\)-th contacts as \(S_i\). By definition of renewal process, the intercontact times \(S_i\) between a given pair of nodes are independent and identically distributed (while they can follow different distributions for different pairs), hence \(S_i \sim S, \text{ for all } i\).

In order to understand how the detected contact process depends on the contact process described above, let us denote with \(S_j\) the time between the \((j - 1)\)-th and the \(j\)-th detected contact and assume that at time \(t_{j-1}\) a contact has been detected, as shown in Figure 1 for case \(j = 1\). Then, the detected intercontact time \(S_j\) is the time from \(t_{j-1}\) until the next detected contact, which can be obtained by adding up the intercontact times \(S_i\) between \(t_{j-1}\) and the next detected contact. Denoting with \(N_j\) the random variable measuring the number of intercontact times between the \((j - 1)\)-th and the \(j\)-th detected contact, we obtain \(S_j = \sum_{i=1}^{N_j} S_i\). Recalling that \(S_i\) are i.i.d. by definition, if \(N_j\) were i.i.d. for all \(j\) and independent of the inter-contact times \(S_i\) occurred before the \((j - 1)\)-th detected contact, then also \(S_j\) would be i.i.d. and the detected contact process could be treated as a renewal process. Unfortunately, it is possible to prove (see [2]) that this is not true in the general case. In particular, \(N_j\) depends on \(Z_{j-1}\), defined as the displacement of the last detected contact in its ON interval (hence it can take values in \([0, \tau]\), see Figure 1) and \(Z_{j-1}\) depends on \(Z_{j-2}\) (the displacement of the second last detected contact). Since \(Z_j\) are not independent, \(N_j\) is not i.i.d. and the detected contact process is, in general, not renewal. However, for the particularly relevant case where intercontact times \(S_i\) are exponential, which we develop in detail in the paper, we

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\(^1\)For example, in [1] we have exploited this result for investigating how to optimally configure the duty cycling process in order to meet a target performance metric.

\(^2\)It has been shown in [11] that, under certain conditions, this strategy is optimal for minimising the probability of missing a contact. However, please note that designing an effective duty cycling scheme is out of the scope of this paper, which focuses only on the effects of duty cycling on intercontact times.

\(^3\)Fine grained synchronisation is not necessary to this end, and time drifts due to clock inaccuracies are perfectly tolerable. For example, in the case of mobile offloading – one of the most popular recent applications of opportunistic networks [12] – this synchronisation can be controlled by the cellular infrastructure.
show that $\tilde{Z}_j$ are i.i.d. and independent of the past evolution of all stochastic processes. Therefore, in this case, the detected intercontact times are a renewal process. For making the analysis tractable, we assume that the same property holds in general. This is a reasonable approximation under the assumption that ON intervals are very short compared to the average intercontact times $E[S]$, which, as discussed later in the paper, is commonly verified in practice. Therefore, in the following we express $S$ as a random sum of i.i.d. random variables, according to the following definition.

**Definition 1.** The detected intercontact time $\tilde{S}$ can be obtained as $\tilde{S} = \sum_{i=1}^{N} S_i$, where $N$ is the random variable describing the number of contacts needed to get one detected.

Random sums of i.i.d. variables have some useful properties, which we will exploit in Section 3.2 in order to derive the first two moments of $\tilde{S}$. Please also note that Definition 1 is general, i.e., holds for any type of continuous intercontact time distribution and for any type of duty cycling policy.

### 3. THE DUTY CYCLING EFFECT ON INTERCONTACT TIMES

In the next sections, building upon Definition 1, we show how the duty cycling model and the contact process can be studied together in order to uncover the features of the detected intercontact times.

#### 3.1 Deriving the distribution of $N$

We start by studying the probability distribution of $N$, defined as the number of contacts needed, after a detected contact, in order to catch the next one. We first discuss the case in which real intercontact times feature a generic distribution with PDF $f(x)$ and CDF $F(x)$, then we solve the case of exponential intercontact times. Recall that we are assuming the detected contact process to be renewal, so we focus on the portion of this process between two detected contacts. Under the renewal assumption, we can focus, without loss of generality, on what happens between the first and second detected contact. Then, the rationale behind the derivation of $N$ is pretty intuitive. In fact, $N = 0$ corresponds to the case where the first intercontact time after a detection ends in an ON interval. For case $N = 1$, the first intercontact ends in an OFF interval, while the following one ends in an ON interval after the point in time when the first intercontact time has finished. All other cases follow using the same line of reasoning (for example, Figure 1 depicts a case where $N=3$). Please note that in the following, ON and OFF intervals will be denoted with $T_{ON}$ and $T_{OFF}$, respectively.

The derivation of the PMF of $N$ in Theorem 1 below quantifies the probability $P(N = k)$. The line of reasoning for deriving this result is as follows (see Figure 2 for a graphical representation). We denote with $X_0$ the time of the last detected contact and we fix $X_0 = t_0$. Let us thus focus on the sequence of contacts after $t_0$ and define random variable $E_k$, which is equal to one when the $k$-th of these contacts is in an ON interval, equal to zero otherwise. It is easy to see that the following holds true:

$$P\left(N = k \mid X_0 = t_0\right) = P\left(E_1 = 0, ..., E_{k-1} = 0, E_k = 1\right),$$

i.e., the $k$-th contact is the first contact detected after $t_0$ if it falls into an ON interval and all previous ones fall in an

**Figure 2:** Example for case $N = 1$ and $N = 2$

OFF interval. In the following we will study cases $N = 1$ and $N = 2$, then $N = k$ follows by analogy.

Let us start with $N = 1$. The above Equation 2 becomes $P(N = 1 \mid X_0 = t_0) = P(E_1 = 1)$, which is equivalent to saying that the first intercontact time has to finish in any of the ON intervals after $t_0$. From Figure 2, we see that this happens when $S_1 + t_0 \in T_{ON}^{k+1}$, where $\cup$ denotes the union operator and $n_1$ the interval in which the first contact takes place. The probability of this event is given by the sum of the probability that $S_1 + t_0 \in T_{ON}^{k+1}$, for all $n_1 \geq 0$. Any ON interval after $t_0$ is in the form $[s_0 + n_1 T, s_1 + n_1 T)$. Therefore, recalling that $F(x)$ is the CDF of intercontact times, the probability that $S_1 + t_0 \in T_{ON}^{k+1}$ for each $n_1$ is given by $F(s_1 + n_1 T - t_0) - F(s_0 + n_1 T - t_0)$. Then, denoting the latter as $p_{n_1}(t_0)$ and summing over all $n_1$ we obtain $P(N = 1 \mid X_0 = t_0) = \sum_{n_1=0}^{\infty} p_{n_1}(t_0)$.

Let us now consider the case $N = 2$. It occurs when the first contact happens during an OFF interval and the second contact during an ON interval, i.e., it occurs with probability $P(E_1 = 0, E_2 = 1)$ (Figure 2). The two events are dependent, since the second contact is constrained to start after the first one. Exploiting the knowledge on the contact process (Figure 2) and denoting with $n_2$ the interval in which the first contact after $t_0$ falls and with $n_2$ the interval in which the second contact happens, we can rewrite the above equation as follows:

$$P\left(S_2 + S_1 + t_0 \in \cup_{n_2=0}^{\infty} \cup_{n_1=1}^{n_2+1} T_{ON}^{n_2} \cap s_0 + n_1 T \right).$$

(3)

We condition on the event $\{S_1 = y_1\}$ and then apply the law of total probability, obtaining $\int_0^\infty P(S_1 = y_1) \cdot P(S_2 + y_1 + t_0 \in \cup_{n_2=0}^{\infty} \cup_{n_1=1}^{n_2+1} T_{ON}^{n_2}) dy_1$. The event $\{S_2 + y_1 + t_0 \in \cup_{n_2=0}^{\infty} \cup_{n_1=1}^{n_2+1} T_{ON}^{n_2}\}$ happens with the same probability of event $\{S_2 + y_1 + t_0 \in \cup_{n_2=0}^{\infty} \cup_{n_1=1}^{n_2+1} T_{ON}^{n_2}\}$ if $y_1 + t_0$ falls in one of the OFF intervals after $t_0$, and with probability 0 otherwise. Therefore, after noting that OFF intervals in which the first contact takes place are of type $[s_1 + n_1 T, s_0 + (n_1 + 1) T)$, Equation 3 can be rewritten as follows:

$$\sum_{n_1=0}^{\infty} \int_{s_1 + n_1 T}^{s_1 + (n_1 + 1) T} P(S_1 = y_1) \cdot P(S_2 + y_1 + t_0 \in \cup_{n_2=0}^{\infty} \cup_{n_1=1}^{n_2+1} T_{ON}^{n_2}) dy_1.$$

(4)

We now characterise $P(S_2 + y_1 + t_0 \in \cup_{n_2=0}^{\infty} \cup_{n_1=1}^{n_2+1} T_{ON}^{n_2})$. The probability of the event $\{S_2 + y_1 + t_0 \in \cup_{n_2=0}^{\infty} \cup_{n_1=1}^{n_2+1} T_{ON}^{n_2}\}$ can be computed following the same line of reasoning used for deriving $P(N = 1)$. Thus, after defining $p_{n_1}(t) \triangleq F(s_1 + n_1 T - t) - F(s_0 + n_1 T - t)$, we can write $P(S_2 + y_1 + t_0 \in \cup_{n_2=0}^{\infty} \cup_{n_1=1}^{n_2+1} T_{ON}^{n_2}) = \sum_{n_1=0}^{\infty} \int_{s_1 + n_1 T}^{s_1 + (n_1 + 1) T} P(S_1 = y_1) \cdot p_{n_1}(t) dy_1$.
Theorem 1 below. Same line of reasoning and it is discussed in the proof of
P we can obtain applying the law of total probability. To this aim, we can
detected contact and, defining \( ˜X \), the following holds:
\[
\sum_{n_2=n+1}^{\infty} P(n_2) = f(y_1) \sum_{n_2=n+1}^{\infty} p_{n_2}(t_0 + y_1)dy_1.
\] (5)

Then, the derivation of the general case \( N = k \) follows the same line of reasoning and it is discussed in the proof of
Theorem 1 below.

Now that we have fully characterised \( P(N = k; \bar{X}_0 = t_0) \) we can obtain \( P(N = k) \) by simply deconditioning, i.e., applying the law of total probability. To this aim, we can
write \( \bar{X}_0 = s_0 + \bar{Z} \), where \( \bar{Z} \) is a distributed contact and it is assumed to feature the same distribution for all detected
contacts. Knowing the distribution of \( \bar{Z} \), one can easily derive that of \( \bar{X}_0 \). The modelling of \( \bar{Z} \) should be evaluated
on a case-by-case basis, depending on the actual distribution of
intercontact times. An approximation that holds in the vast majority of real scenarios is discussed in the proof of
Theorem 1 below.

Now we can finally state Theorem 1, which characterises the
PMF of \( N \).

**Theorem 1** (Distribution of \( N \)). When \( E[S] \gg T \), the probability mass function of \( N \) can be approximated by the following:
\[
P(N = k) = \int_{s_0}^{s_1} f_{X_0}(t_0) P(N = k; \bar{X}_0 = t_0)dt_0,
\] (6)
where \( \bar{X}_0 = s_0 + \bar{Z} \) characterises the time instant of the last
detected contact and, defining \( p_{n_1}(t) \equiv F(s_1 + n_1 T - t) - F(s_0 + n_1 T - t) \), the following holds:
\[
P(N = 1; \bar{X}_0 = t_0) = \sum_{n_1=0}^{\infty} p_{n_1}(t_0)
\] (7)
\[
P(N = 2; \bar{X}_0 = t_0) = \sum_{n_1=0}^{\infty} \int_{s_0 + (n_1 + 1) T - t_0}^{s_1 + n_1 T - t_0} f(y_1) \sum_{n_2=n_1+1}^{\infty} p_{n_2}(t_0 + y_1)dy_1
\] (8)
\[
P(N = k; \bar{X}_0 = t_0) = \sum_{n_1=0}^{\infty} \cdots \sum_{n_k=n_{k-1}+1}^{\infty} \int_{s_0 + (n_1 + 1) T - t_0}^{s_1 + n_k T - t_0} f(y_1) \cdots \int_{s_0 + (n_{k-1} + 1) T - t_0 - \sum_{i=2}^{k-1} y_i}^{s_1 + n_k T - t_0 - \sum_{i=1}^{k-1} y_i} f(y_{k-1}) \cdot p_{n_k}(t_0 + \sum_{i=1}^{k-1} y_i dy_{k-1} \cdots dy_1). \] (9)

**Proof.** Cases \( N = 1 \) and \( N = 2 \) have been discussed
above and will not be further considered. As anticipated, the derivation for case \( N = k \) with \( k > 2 \) follows the same line of reasoning of the previous cases. The only difference is that, for
\( N = k (k > 2) \), in order to make the analysis tractable, we need to introduce an approximation. Specifically, we neglect the case of two consecutive contacts falling in the
same OFF interval. This choice is justified by a property that holds in the vast majority of real scenarios, i.e., that
the average duration of the real intercontact times is much
larger than the duty cycling period (i.e., \( E[S] \gg T \)). The implication of this property is that the probability of having
two consecutive real contacts in the same OFF interval is
very low, hence negligible. When this property holds, it is possible to simplify Equation 6. Since \( \bar{X}_0 = s_0 + \bar{Z} \),\nwith Equation 6 we are taking into account the effect of the
placement \( \bar{Z} \) on \( N \). However, we know that \( \bar{Z} \) varies in \([0, \tau]\), while \( E[S] \gg T \) also implies \( E[S] \gg \tau \). Then, consider for the sake of simplicity case \( N = 1 \) (the same line of reasoning applies to all other cases),
which corresponds to \( P(S_1 + X_0 \in \cup_{n=0}^{\infty} T^{ON}_{n+1}) \). We can rewrite it as \( P(S_1 + s_0 + \bar{Z} \in \cup_{n=0}^{\infty} T^{ON}_{n+1}) \). However, since \( E[S_1] \gg E[\bar{Z}] \), we can assume that \( \bar{Z} \) is negligible. Hence, \( P(N = k) \) can be simply obtained from Equation 7-9 after setting \( t_0 \) equal to an arbitrary point in \([s_0, s_1]\), e.g., \( t_0 = s_0 \).

Theorem 1 provides an accurate approximation of the
PMF of \( N \) when the probability of two undetected contacts falling in the same OFF interval is very low. In Section 3.2 we show that the condition under which this assumption
is reasonable is satisfied by the most popular traces of human
contacts. Despite this approximation, finding a closed form
for the distribution of \( N \) in Theorem 1 might be prohibitive
in the general case, and we have been able to obtain only
numerical solutions. However, when intercontact times are
exponential, a closed form solution for the PMF of \( N \) is available (Corollary 1 below, whose proof can be found in [2]),
from which the first two moments of \( N \) can be computed
using standard probability theory.

**Corollary 1** (\( N \) in the exponential case). When \( \text{real intercontact times } S_i \text{ for a tagged node pair are exponential}^5 \text{ with rate } \lambda \), the probability density of \( N \) is given by:
\[
|P(N = 1) = 1 + \frac{e^{-\lambda \tau}}{\lambda} + \frac{e^{\lambda (1-e^{-\lambda \tau})}}{\lambda (e^{\lambda \tau}-1)} \]
\[
P(N = k) = e^{\lambda \tau} \frac{(1-e^{-\lambda \tau})^k}{\lambda (e^{\lambda \tau}-1)^k}, k \geq 2
\] (10)

Please note that condition \( E[S] \gg T \), required by Theorem 1, in the exponential case of Corollary 1 becomes \( \lambda T \ll 1 \). In [2] we have verified analytically the error introduced by this approximation.

3.2 Deriving \( \bar{S} \)

Exploiting the results in the previous section, here we discuss
how to compute the first and second moment of the
detected intercontact time \( \bar{S} \) for a generic node pair \( A, B \).
The relation between \( S \) and \( \bar{S} \) is stated by Definition 1, i.e.,
\( \bar{S} = \sum_{i=1}^{N} S_i \). Thus, \( \bar{S} \) is a random sum of random variables,
and we can exploit well-known properties to compute its
first and second moment (in [2] we also specialise this result
for the exponential case).

**Proposition 1.** The first and second moment of \( \bar{S} \) are

While the above formula holds in general, in the case of
exponential intercontact times it is possible to derive an even
\(^5\)For ease of notation, for \( \lambda \) we omit the subscript indicating the specific node pair considered. Please note, however, that
the network model we are referring to is still heterogeneous.
stronger result, described in Theorem 2 below. This result is the key derivation of this work, and it tells us that, under condition $\lambda T \ll 1$, exponential intercontact times are modified by duty cycling only in terms of the parameter of their distribution but they still remain exponential.

**Theorem 2.** When $\lambda T \ll 1$, the detected intercontact times $\tilde{S}$ follow approximately an exponential distribution with rate $\lambda\Delta$.  

**Proof.** We can calculate the moment generating function (MGF) of $\tilde{S}$ using the expression described at the beginning of the section, i.e., $M_S(s) = M_N(M_S(s))$. First of all, we have to calculate the MGF of $N$, that we can obtain from Equation 10. In fact, recalling $\tau = T\Delta$, we have

$$M_N(s) = \sum_{k=0}^{\infty} s^k \cdot P\{N = k\} =$$

$$= s \left[ 1 - \frac{1 - e^{-\lambda T\Delta}}{\lambda T\Delta} + e^{\lambda T\Delta} \left( 1 - e^{-\lambda T\Delta} \right)^2 \right] +$$

$$+ s^2 \frac{e^{\lambda T\Delta} \left( 1 - e^{-\lambda T\Delta} \right)^2}{\Delta (e^{\lambda T\Delta} - 1)} - \frac{1 - \Delta}{\Delta (e^{\lambda T\Delta} - 1)} - e^{\lambda T\Delta} - 1 - \lambda T \sigma (1 - \Delta).$$

As we are in the hypothesis $\lambda T \ll 1$, we can use the Taylor expansion to find that $M_N(s) = s\Delta + s^2 \frac{\Delta(1-\Delta)}{\lambda - s\Delta} + o(1)$. As the MGF of an exponential distribution $S$ is given by $M_S(s) = \frac{\lambda\Delta}{\lambda - s}$, we obtain the following:

$$M_S(s) = \frac{\lambda\Delta}{\lambda - s} - s^2 \frac{\Delta(1-\Delta)}{\lambda - s\Delta} + o(1) =$$

$$= \frac{\lambda\Delta}{\lambda - s} + o(1).$$

Since the above equation corresponds, approximately, to the MGF of an exponential random variable with rate $\lambda\Delta$, we conclude that $\tilde{S}$ can be approximated as an exponential random variable with rate $\lambda\Delta$. A longer version of this proof is provided in [2].

In order to validate the assumption $\lambda T \ll 1$, we consider four popular datasets often used in the related literature (and publicly available at http://crawdad.cs.dartmouth.edu/): Infocom05, Infocom06, RollerNet, and Reality Mining. The average contact rates estimated from these traces are, respectively, $3.2 \times 10^{-4} \text{ sec}^{-1}$, $1.13 \times 10^{-4} \text{ sec}^{-1}$, $4.07 \times 10^{-4} \text{ sec}^{-1}$, and $1.2 \times 10^{-6} \text{ sec}^{-1}$. Thus, considering $T$ values around 100s, identified in [10] as a good trade-off between energy efficient and accuracy in contact detection, $\lambda T$ remains below 1 for all these datasets.

4. RELATED WORK

In the literature, the works closest to ours are [13] [8]. Our contribution is more general than [13] as it is not bound to the RWP model but it can be applied to any well known distribution for intercontact times, if numerical solutions are sufficient, or it can be solved in closed form for the heterogeneous exponential case. Moreover, despite its simplicity, our duty cycling function with ON/OFF states allows for more flexibility than the simple scanning every $T$ seconds, as done in [13]. Qin et al. [8] perform a study that is exactly orthogonal to this work. In fact, they evaluate how link duration (or contact duration, in our terminology) is affected by the contact probing interval. We investigate the effect of duty cycling (which, as already discussed, can be easily translated into a contact probing problem) on the intercontact time rather than on the contact time. The motivation for this choice is that intercontact times are typically much larger than contact times in real human mobility, thus the delay in opportunistic networks is mainly determined by the intercontact time. Intercontact times are larger when contacts are not detected immediately or missed and thus it is important to understand how they increase and how this affects the delay experienced by messages.

5. CONCLUSIONS

In this work we have investigated the effects of duty cycling on intercontact times, delay, and energy consumption in opportunistic networks. To the best of our knowledge, this is the first contribution that evaluates the actual effects of duty cycling on the forwarding opportunities between nodes. To this aim, we have provided a general formula for the derivation of the intercontact times under duty cycling, and we have specialised this formula obtaining a closed-form expression for the case of exponential intercontact times. Surprisingly enough, under condition $\lambda T \ll 1$ (satisfied by most popular contact datasets), the intercontact times after duty cycling can be approximated as exponentially distributed with a rate scaled by a factor $\frac{1}{\Delta}$.

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7. REFERENCES