Evaluating the Performance of Social Networks of Sensors under Different Mobility Models

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***Abstract*—Sensor Networks are becoming ubiquitous in our society due to their broad applicability to data intensive tasks such as keeping air population to safe levels, efficient communication in military applications, to mention but a few. Furthermore, we have seen the emergence of sensor technology being integrated in everyday objects such as cars, traffic lights, phones, and even being attached to living beings such as dolphins, birds and humans. The consequence of this widespread use of sensors is that new sensor network infrastructures may be built out of static and mobile nodes. When mobility is a variable one should define which mobility model is best for the infrastructure given their differences. This paper evaluates which mobility pattern is best suited to be used in a Social Network of Sensors (SNoS). We evaluate several mobility models and measure the efficiency of information flow in a SNoS if mobile sensors follow these mobility patterns. The paper provides us with a greater understanding of the benefits of mobility in realistic scenarios.**

I. Introduction

Sensor networks have taken an increasing practical relevance to society, and the number of deployed sensor network infrastructures is now hard to quantify [1]. Once in place, these sensor infrastructures could be exploited to improve many of the tasks we require done today such as monitoring of crime, prevention of forest-fires, tornado-warning systems, etc. When connected and mobile, these sensors form a "Social Network of Sensors" (SNoS) where the "Social" aspect comes from the movement of "Things" endowed with sensing capability such as smart phones, inboard navigation systems, and other smart objects brought around by humans, vehicles, or even animals.

So it should be clear that one of the aspects of SNoS that makes them different from traditional sensor network infrastructures is that some of these sensors can be mobile *without requiring any energy to achieve mobility* because they are carried by objects that are naturally moving around: taxis, humans, birds, etc. As a consequence of such mobility, these nodes can be very effective in SNoS given that they can be dynamically patrolling and monitoring the environment. Mobile nodes in SNoS are extremely valuable in locations where there is not any (or enough) smart objects to opportunistically exploit the environment, and where deployment of dense-enough wireless sensor nodes would not possible or economically feasible. It should be clear than that the understanding of different mobility patterns in the context of sensor networks should help us design more efficient infrastructures. Moreover, the mobility is surely to be coupled with fixed sensors which makes the understanding of the benefit of mobility even more important given different mobility patterns lead to different interaction patterns between mobile and static sensors.

In this work, we evaluate the performance of three of the most studied mobility models in the literature: Lévy Flight [2], CTRW (Continuous-Time Random Walk) [3], and preferential return as proposed by Song et al. [4]. We study their effect to SNoS composed of both mobile and static sensors. Using a number of simulation experiments, we have tried to understand the effect of the aforementioned models to the performance of a realistic SNoS. The main results we have shown are the following. First, in dense networks the performance change between different mobility models is small. Second, sensor radius impact is bigger than sensor density thus it should be maximized. Third, human mobility model performs poorly compared to other mobility models due to his big wait-time cutoff and the preferential return which may pose a big challenge in the engineering of sensor networks that take advantage of human mobility.

II. Related Work

A. Sensor Networks

Most of the works on sensor networks are on coverage, protocols, and algorithms to reposition sensors in the environment [5], [6]. The difference between these works is on how the desired positions of sensors are computed. Typically, mobility is only exploited to achieve a static optimal reconfiguration in an enlarged sensing environment rather than in an environment where the dynamics of sensors' movements are exploited as an added characteristic of the sensor infrastructure [7].

Liu et al. [8] show that sensor mobility can be exploited to effectively reduce the detection time of a stationary intruder. They point out that given a fixed number of sensors, their coverage area is inherently bound by the density of sensors. However, if sensors are allowed to move, the area that can

be covered increases because sensors are now able to reach locations in the environment that would have never been covered. The authors's work is only for random movements.

B. Mobility Models

In 1947, the French mathematician Paul Pierre Lévy proposed a new type of randomization method based on a specific kind of probability distribution: heavy-tailed. The proposed method has been shown to be useful in simulations for random or pseudo-random natural phenomena. Indeed, scientist have used Lévy movement to describe the flight pattern of wandering albatrosses [9] and the foraging patten of spider monkeys [10].

CTRW is a random walk that includes random waiting times between jumps. A case where the distribution of waiting times has infinite variance (e.g.,power law) was treated in [11] and it has been used by Brockmann et al. [12] to describe the scaling laws for the flow of bank notes and then to infer the dynamics of human travels.

Today it is generally understood that human mobility patterns are non-random. Song et al. [13] has proposed a model for human mobility based on preferred locations, not fixed *a priori*, but rather emerging as a consequence of the mobility process. Their model is based on two generic mechanisms, exploration and preferential return, both unique to social human mobility and missing from the traditional random-walk (Lévy-flight or Continuous-Time Random Walk) models:

Exploration: a scaling law is proposed to indicate that the tendency to explore additional/new locations decreases with time.

Preferential Return: in contrast with random-walk-based models where people move randomly thus resulting in a uniform distribution of visits, humans show significant propensity to return to previously visited locations, such as their home or workplace.

This model is able to capture most of the characteristics of human mobility, thus we chose it as our reference human mobility model.

It is clear that at all the models above have applicability (some more than others) in the real world and represent movement of some natural or artificial entity. Our assumption is that mobility is achieved for free since sensors are attached to mobile entities. Hence evaluating these more common models enable us to make design decisions.

III. Simulation of Mobility Models in SNoS

Our simulations focus on two aspects. First, we compare the performance of different mobility models in an urban SNoS with both fixed and mobile sensors. In particular, we focus on the benchmarking of two issues in sensor networks: *(i)* the time t_D to detect an event (source) in the environment, and *(ii)* the time t_R to report that event to a specific location (sink) in the environment. Our ultimate goal is to find how much the mobility model affects performance and if there is a threshold in sensor density after which the mobility model is less relevant to the performance. Second, we show how to deploy a SNoS in a realistic environment (based on population density) and the performance that could be expected.

A. The Model

The simulations were run on the simulator developed for our previous work [14] where we studied the effect of human dynamics. The reason to choose a city-wide setup is that people live in cities. The city is the best environment to achieve mobility for free, by assuming that sensors are carried by mobile entities, due to the abundance of mobile carriers (e.g., people, vehicles).

The environment is a square divided in square patches of one unit area. Static and mobile sensors are deployed in the environment differently. Static sensors are deployed in a regular lattice simulating the existing infrastructure. Mobile sensors follow an exponential distribution from the center of the environment to simulate the characteristic population distribution of some metropolis [15]. Sensors move at a constant speed of 1 unit per tick. There are two special markers in the environment called the *event* and the *sink*. The event is the item we want to detect (e.g., a fire, an explosion) whereas the sink is the place to which report the event (e.g., a police station). We placed the sink and the event in the environment at a distance to be equivalent to having them in the periphery of the city.

In the simulation, mobile sensors move according to a specified model, exploring the environment thus increasing the ratio of covered area $f_a(t), t \in \mathbb{N}$ that is the number of covered locations divided by the total number of possible locations (ℓ^2) where ℓ is the side of the square lattice representing the environment. A location is considered visited if it was reached by at least one sensor node during the execution of the simulation. At some point during the execution of the simulator a sensor should detect the event. From that point onwards the simulator changes mode with the goal of spreading information about the detected event to other sensors when they are within communication range. The simulation stops when one of the sensors with the information about the event finds the sink node.

B. Comparing Different Mobility Models

The simulator is executed using different kinds of random walks—Lévy walk and CTRW—and these are compared against the model proposed by Song et al. [13]. Song's model has many parameters. Scaling parameters represent exponents of power laws of jump length and wait time. Cutoff parameters control the point at which exponential cutoffs happen. Preferential return is governed by the parameters ρ and γ (see [13] for detailed description of the meaning of these parameters). We used the following values: jump length scaling parameter $\alpha = 0.55$, jump length exponential cutoff $k_1 = \ell/10$, wait time scaling parameter $\beta = 0.8$, wait time exponential cutoff $k_2 = 5\ ticks$, scaling of preferential return $\gamma = 0.21$, preferential return probability weight $\rho = 0.6$.

Lévy walk and CTRW use the same scaling parameters of Song's model for power-law distribution of jump length.

Lévy walk does not have a wait time while CTRW uses Song's power law with exponential cutoff for wait time to be consistent with our previous results [14]. Since CTRW and Song's models can be reduced to Lévy walk (setting wait time to 0 in CTRW, setting both wait time and preferential return probability to 0 in Song's model), we can say that Lévy walk represents the best theoretical performance for these kind of random walks.

C. Estimating Real-World Performance

We fixed the size environment of side $\ell = 100$, then we calculated the number of static sensors $n_s = 441$ according to:

$$n_s = k^2,\ k = (\ell + r)/r \tag{1}$$

where r represents the radius of transmission in a square lattice of side ℓ. These static sensors represents the existing infrastructure which is attached to e.g., buildings and streetlights.

In order to simulate a real world scenario, it makes more sense to look at densities that are realistic with regards to "things" carrying them. Focusing primarily on human mobility we set to work under conditions that resemble densities of typical urban areas in the USA.

We started by matching the size of the simulation environment to a meaningful size of a city. We set the size of the square lattice $\ell = 10\,\text{km}$, which makes the simulation area to be $A = 100\,\text{km}^2$ and then we define the unit area a inside simulation environment as a square of 10×10 patches ($1\,\text{km}^2$ in real terms). Once the environment had a real size we set the sensor radius to match real world technologies, in our case we chose Bluetooth that has a range of about 10 meters, which is equivalent to $r = 0.1$ in a simulation environment. We assume a boolean sensor network (where the event is either detected or not) with fixed sensor radius r both for mobile and static sensors, we can argue that an event can be detected if and only if the event is located at a distance, $d \leqslant r$.

Given this setup we now know that one discrete unit of space in the environment is $1\,u = 100\,\text{m}$, then we also know sensors move at a constant speed of $1\,u/\text{tick} = 100\,\text{m/tick}$.

We then tried to match the time unit (1 tick) with an equivalent in the real world. If we assume that mobile sensors are carried by pedestrians with an average constant speed of 5 km/h then it is easy to see that 1 tick equals 1.2 minutes in real time which gives us that 1 hour is equivalent to 50 ticks. We can now give a real meaning to the wait-time cutoff k. We used 2 configurations: the first has $k_2 = 5$ ticks to show the impact of sensor radius on performance while the second case uses $k_2 = 17\,\text{h}$ as found in [13].

The next step is to compute the number of mobile sensors n_m. From Equation 1 we can see that achieving a perfect coverage with only static sensor is truly impossible since it would require more than a million static sensors to cover our simulation environment. Hence, mobile sensors represent the *only practical way* to implement a SNoS at a city level. The objective here is not to find the number of mobile sensors to achieve best possible performance, but to reach a certain event delivery ratio in a given amount of time, as a tradeoff between performance and the effort needed to involve a lot of people. We can obtain the number of mobile sensors required from the population density of the city. As a reference city density RD we took the average city densities of 690 cities of the developed world with a population greater than 500,000 people as indicated in [16]. Then, the number of mobile sensors n_m is given by:

$$n_m = \frac{x \cdot RD \cdot A}{a} - n_s \tag{2}$$

where $x \in X \subseteq [0, 1]$ represents the fraction of reference density we consider. We took different percentages, X = {0.01, 0.015, 0.02, 0.025, 0.035, 0.05, 0.07, 0.09, 0.11, 0.13, 0.15, 0.175, 0.2}, of reference density $RD = 2000\ ppl/km^2$ and observed the event delivery ratio to the sink, that is how many runs out of 500 ended before reaching the time limit, given different time constraints (4h, 5h, 6h, 8h, 10h). We provide the mean of each of the values and the standard error of the mean (SE) that quantifies the variance in the performance of the sensor network that may arise due to the stochastic nature of sensors deployment and movements.

IV. Experimental Results

A. Mobility Model Performance

If we look at the performance guaranteed by different kinds of mobility models, we see in Table I that detection time follows a law of the kind $t_D(n_m) = an_m^{-b}$ where a and b are constants. Note that the behavior is the same for the all four different models except for the values of a and b (as also seen in Fig. 1). Table I also reports the performance for the report time, $t_R(n_m)$, which is also defined by an equation similar to $t_D(n_m)$ and again followed by all mobility models.

As a first observation we can see that there is no big difference between Lévy walk and CTRW so we can argue that the impact of waiting time to the performance in SNoS is limited. This was expected because the wait-time cutoff is quite small. Moreover the wait-time distribution is such that most pauses have a limited time length with few long pauses, thus at any moment in time most sensors are able to move. This experiment lead us to argue that increasing the wait-time cut off should degrade performance only slightly.

What is most interesting however is that as the sensor density increases the difference in performance between different mobility models also decreases becoming essentially irrelevant. We must stress that this is not a consequence of the interaction with static sensors, which are almost irrelevant given the small sensor radius and very limited number. Instead it is due to the influence which higher density has on mobile sensor inter-contact time. This result is important because it tell us that in a sufficiently dense network, the performance is not bounded by a specific mobility model but by sensor speed and protocol in charge of delivering information. Here we have used epidemic spreading, that is the protocol with highest (optimal) performance, so we ruled out spreading protocol as limiting factor.

However, if we look at "coverage" as the main factor, the mobility model used has a greater impact because the area covered depends heavily on the mobility of sensors. As the sensors move, they are able to "see" areas of the environment that would otherwise not be seen. This accounts for a fraction of the area visited/covered by the mobile sensors. Fig. 3 shows the fraction of the area covered at the end of the simulation (i.e. $t_{sim} = t_D + t_R$) as we increase the number of mobile sensors. As expected, Lévy walk and CTRW have the best coverage since there is no preferential return or cut off in jump length thus sensors spread rapidly in the environment following a super diffusive process [17]. Song's model behave like a sub-diffusive process [18], thus should have a worse coverage than those model. However, the preferential return in Song's model has a smaller impact at the beginning of the simulation, because the probability of a jump to previously unseen locations is higher and this factor partially balances the progressive diffusion slowdown as the time goes by.

Song's model instead of being approximately linear it increases following a law of the kind $a + b\ln(n_m)$, where a and b are constants (Fig. 3). This is caused by a saturation, that is, it is increasingly harder to achieve a greater coverage by simply adding more sensors because they are not uniformly distributed in the space; hence the edges of the environment are less likely to be covered compared to locations in the center of the environment. However we must say that if we allow the simulation to run indefinitely, there will be a time instant t_{sim} such that the fraction of covered area $f_a(t_{sim}) = 1$. This led us to another observation: due to the large amount of people and high density of metropolitan cities, with just a relatively small percentage of the population it is possible to build a SNoS with a very good coverage. However, performance relative to t_D and t_R does not scale as well as we increase the number of mobile sensors. This is a problem because it limits the efficacy of the network and its usefulness in cases where a high delay of information delivery can be tolerated (e.g., tracking of animals, street/place mapping).

B. Real World Performance

If instead of looking at performance we focus on density aspects more interesting observations can be made (Figs. 4 and 5). First we see that once a small density threshold is exceeded, the event delivery ratio increases sharply; this could depend on the epidemic spread of the event or it is a property of the network itself. That is, the percolation threshold of the network is small, thus even if very few sensors find the event directly, it rapidly spreads over the network to reach the sink.

Second, once we reach an upper threshold, the event delivery ratio tends to saturate. Therefore it may not be convenient aim for a perfect delivery ratio, because the effort to obtain it (the number of mobile sensors required) grows faster than the percentage of reported events in time t_{sim}. These two observations match well with the fact that data is fitted almost perfectly by a Gompertz function [19], which is a sigmoid function where growth is slower at the start and end, but the upper asymptote of the function is approached much more

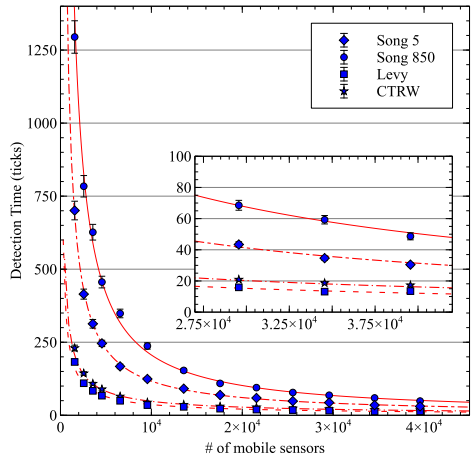

Fig. 1. Detection Time t_D follow the law $t_D \sim an_m^b$ but scaling exponent b is smaller than the setup with radius $r = 2.5$.

gradually by the curve than the lower asymptote, in contrast to the simple logistic function in which both asymptotes are approached by the curve symmetrically. The equation re-parameterized according to [20] is:

$$A \cdot exp\Big\{ - exp\Big[\frac{\mu \cdot e}{A}(\lambda - t) + 1\Big]\Big\}, \quad e = exp(1) \qquad (3)$$

where A is the upper asymptote, λ is the length of the lag phase and μ is the max growth rate. In our case, $A = 100$ and λ is a density, instead of a time, that may represent the percolation threshold of the network. Both λ and μ depend on the time constraint on t_{sim}. Moreover, we observe that the asymmetry is bigger for small values of t_{sim}.

Third, unfortunately the wait time cutoff has a *big* impact on the delivery ratio under time constraints (Fig. 5). This can be explained by the fact that it increase both the average value and the variance of t_{sim} thus the network does not perform consistently. This behavior represent a major problem since is affected by the max grow rate μ that is the delivery ratio increase slower than wanted as we add sensors, thus requiring high densities or we must relax time constraints. Last, the density required to achieve the necessary performance tell us the fraction of the population of the city that should be involved to build the wanted network. This is especially important since it imposes a lower limit on the size and density of the population of the city.

We can expect that in small cities it is not possible to achieve some acceptable performance in a SNoS. Data for some of the biggest cities in the USA is shown in Table II; it should be noted that USA cities have usually a lower density than other metropolis especially if compared to South America or Asia metropolis thus they represent a worst case scenario.

V. Conclusion and Future Work

We found that in dense networks the differences in performance between mobility models fade out if we consider the detection time t_D and the report time t_R. Moreover, we

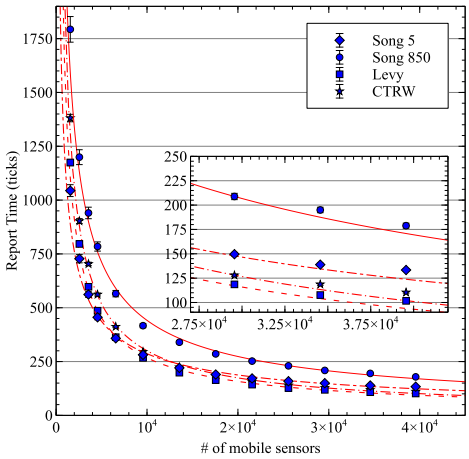

Fig. 2. Report Time t_R follow the law $t_R \sim cn_m^d$ but scaling exponent d is smaller than the setup with radius $r = 2.5$.

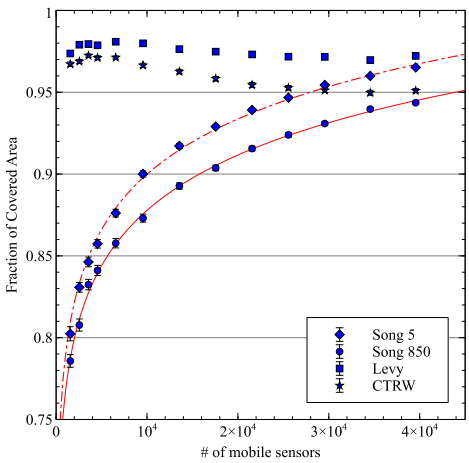

Fig. 3. In Song's model the Fraction of Covered Area $f_a(t_{sim})$ is proportional to $f_a(t_{sim}) \sim a + bln(n_m)$. This means that a saturation occurs while we approach a total coverage.

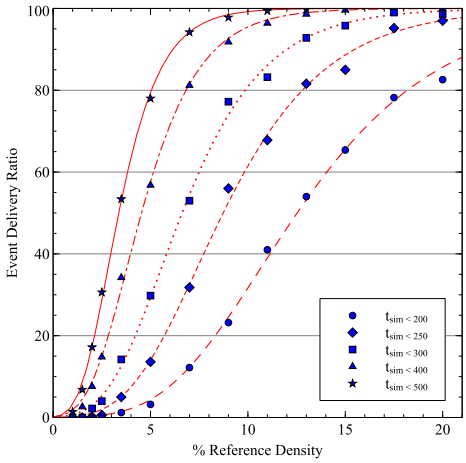

Fig. 4. Event delivery ratio for Song's model with wait time cutoff $k = 5$ follow a Gompertz function.

TABLE I

PERFORMANCE OF A NETWORK SIMULATING A REAL WORLD SCENARIO. DENSITY EVEN IF SHOWN AS ppl/km^2 REPRESENTS SENSOR DENSITY. DETECTION TIME t_D AND REPORT TIME t_R ARE SHOWED IN SIMULATION TICKS. FRACTION OF COVERED AREA $f_a(t_{sim}) \in [0, 1]$.

ppl/km^2	n_m	t_D	SE_{t_D}	t_R	SE_{t_R}	$f_a(t_{sim})$	SE_{f_a}
Song (wait time cutoff $k = 5$)							
20	1559	700.77	31.87	1044.00	27.59	0.8024	0.0043
30	2559	414.63	17.17	727.62	19.09	0.8308	0.0030
40	3559	313.12	14.77	561.35	13.36	0.8463	0.0030
50	4559	246.06	10.75	455.58	11.50	0.8574	0.0026
70	6559	167.26	7.79	357.89	7.42	0.8761	0.0024
100	9559	124.17	5.97	281.16	5.08	0.9001	0.0019
140	13559	91.05	3.79	220.53	3.69	0.9172	0.0015
180	17559	69.37	2.86	189.87	2.97	0.9290	0.0012
220	21559	59.16	2.54	171.69	2.40	0.9392	0.0011
260	25559	48.39	2.01	158.74	2.14	0.9467	0.0009
300	29559	43.40	1.79	149.58	1.84	0.9544	0.0008
350	34559	34.63	1.36	138.83	1.59	0.9600	0.0006
400	39559	30.46	1.24	133.36	1.52	0.9652	0.0006
Song (wait time cutoff $k = 850$)							
20	1559	1294.74	55.55	1793.11	59.50	0.7858	0.0039
30	2559	783.83	36.70	1199.43	34.55	0.8077	0.0037
40	3559	626.54	26.86	940.32	26.74	0.8324	0.0032
50	4559	455.89	20.00	784.37	21.34	0.8411	0.0031
70	6559	348.47	14.73	565.46	14.74	0.8577	0.0029
100	9559	237.08	10.79	416.62	9.61	0.8731	0.0024
140	13559	153.46	6.79	339.75	7.04	0.8927	0.0019
180	17559	109.07	4.72	285.57	5.46	0.9037	0.0017
220	21559	94.63	4.33	252.15	4.54	0.9156	0.0015
260	25559	77.91	3.82	230.12	3.79	0.9240	0.0013
300	29559	68.55	3.17	208.82	3.23	0.9309	0.0012
350	34559	59.28	2.71	194.98	2.80	0.9397	0.0010
400	39559	48.64	2.26	178.86	2.57	0.9436	0.0010
CTRW (wait time cutoff $k = 5$)							
20	1559	230.04	9.90	1381.07	17.33	0.9672	0.0013
30	2559	143.45	5.55	902.68	11.25	0.9688	0.0012
40	3559	108.16	4.46	703.52	8.00	0.9724	0.0010
50	4559	89.13	3.16	561.42	6.65	0.9711	0.0012
70	6559	64.43	2.31	411.91	4.57	0.9712	0.0009
100	9559	43.88	1.39	295.58	3.09	0.9664	0.0013
140	13559	36.22	1.16	223.78	2.25	0.9626	0.0014
180	17559	30.07	1.00	182.00	1.74	0.9583	0.0014
220	21559	27.40	0.88	156.23	1.45	0.9544	0.0016
260	25559	23.25	0.75	139.91	1.18	0.9527	0.0014
300	29559	20.89	0.66	127.94	1.12	0.9512	0.0013
350	34559	18.69	0.67	118.67	1.01	0.9497	0.0015
400	39559	17.26	0.57	110.37	0.78	0.9509	0.0013
Lévy Walk							
20	1559	182.37	7.57	1174.51	14.57	0.9737	0.0012
30	2559	109.69	4.42	796.20	8.55	0.9791	0.0007
40	3559	83.59	3.25	597.33	6.17	0.9795	0.0007
50	4559	67.07	2.82	486.16	5.44	0.9787	0.0009
70	6559	49.59	1.98	363.39	3.64	0.9809	0.0006
100	9559	35.08	1.17	267.13	2.50	0.9799	0.0007
140	13559	28.84	0.97	198.30	1.87	0.9764	0.0009
180	17559	22.60	0.75	163.95	1.43	0.9748	0.0009
220	21559	19.46	0.62	142.88	1.24	0.9731	0.0010
260	25559	17.97	0.60	127.07	1.06	0.9717	0.0009
300	29559	15.91	0.55	118.59	0.95	0.9716	0.0009
350	34559	13.14	0.48	107.66	0.79	0.9697	0.0009
400	39559	13.51	0.46	101.66	0.70	0.9722	0.0008

showed that sensor radius has a bigger impact on them than sensor density, thus it should be maximized, if it is possible. Finally, the delivery ratio to the sink is negatively influenced by wait time and preferential return, thus human mobility model has performance significantly worse than the other mobility models tested.

Network performance is of great interest and presently could be the biggest obstacle in the real implementation since it seems that network latency remain high no matter how many mobile sensors we use.

In order to overcome the aforementioned limitation we have worked on some approaches that could vastly improve this

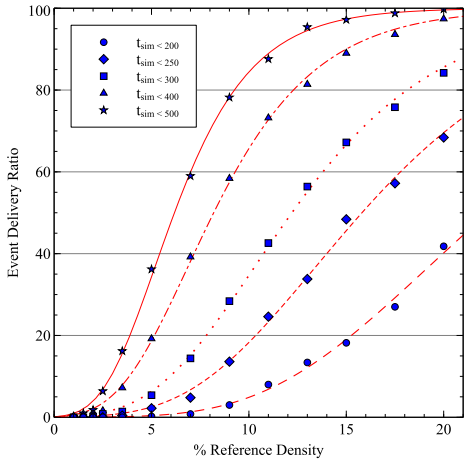

Fig. 5. Event delivery ratio for Song's model with wait time cutoff $k = 850$ follow a Gompertz function.

TABLE II
DENSITIES D OF SOME OF THE BIGGEST USA CITIES AND DENSITY PERCENTAGE REQUIRED TO ACHIEVE THE SENSOR DENSITY OF THE CASE $\%RD = 20$. EVEN FOR SOME BIG CITIES A LARGE PERCENTAGE OF THE POPULATION NEED TO BE INVOLVED THUS THE DEPLOYMENT AND IMPLEMENTATION OF THE SNOS MUST BE CAREFULLY DESIGNED.

$City$	$D(ppl/km^2)$	$20\frac{RD}{D}$
New York, NY-NJ-CT	1800	22.22
Los Angeles, CA	2400	16.67
Chicago, IL-IN-WI	1300	30.77
Philadelphia, PA-NJ-DE-MD	1100	36.36
Boston, MA-NH-RI	800	50.00
Miami, FL	1800	22.22

aspect but that we have not explored here due to space limits. In summary though, a first idea is derived from the fact that the presented realistic setup uses mobile and static sensors that have the same connectivity range. In this configuration, static sensors have no more relevant meaning since they do not significantly participate in detection and delivery, they simply do not cover any meaningful area. Then we could deploy instead, very few expensive static sensors that exploit current infrastructure, so that do not have power constraints and they can have a bigger sensing radius. This way they can function as a gateway for mobile sensors that have a very small range.

A second idea is to rely on the current network infrastructure for static sensors so that they constitute a connected network working at "0 latency" and representing a short path to the sinks. This approach has also the benefit to vastly reduce the memory pressure on mobile sensors because they can hand off as much data as they can to the static sensors that then become responsible for forward the data to the sink. In a city with many Wi-Fi hotspots we believe this may be very effective.

Finally, we can mitigate the impact of sensor radius using a different technology for wireless communications. Indeed Bluetooth is infrequently used by smartphone users while most of the time Wi-Fi is turned on and thus accessible. Moreover, in this kind of devices, battery consumption is not something that is really enforced since users charge their devices almost daily. Wi-Fi has a greater range and performance than Bluetooth and it retains backward compatibility while improving performance in each new version. It also allows the creation of ad-hoc networks and development of automatic configuration protocols (e.g., Zeroconf). Ubiquity and current availability make Wi-Fi the best candidate for an efficient SNoS.

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