An Analytical Model Based on Population Processes to Characterise Data Dissemination in 5G Opportunistic Networks

Enrique Hernández-Orallo *Member, IEEE*, Marina Murillo-Arcila, Juan-Carlos Cano, Carlos T. Calafate, J. Alberto Conejero, Pietro Manzoni *Senior, IEEE*

The scarcity of bandwidth due to the explosive growth of mobile devices in 5G makes the offloading messaging workload to WiFi devices that use opportunistic connections, a very promising solution. Communications in mobile opportunistic networks take place upon the establishment of ephemeral contacts among mobile nodes using direct communication. In this paper we propose an analytical model based on population processes to evaluate data dissemination considering several parameters such as user density, contact rate, and the number of fixed nodes. From this model we obtain closed-form expressions for determining the diffusion time, the network coverage and the waiting time.

Newer 5G wireless technologies like WiGig can offer multi-gigabit speeds, low latency, and security-protected connectivity between nearby devices. We therefore focus our work on the impact of high-speed and short-range wireless communications technologies for data dissemination in mobile opportunistic networks. Moreover, we test whether the coexistence with a fixed infrastructure can improve content dissemination, and thus justify its additional cost.

Our results show that, when user density is high, the diffusion is mainly performed through the opportunistic contacts between mobile nodes, and that the diffusion coverage is close to 100%. Moreover, the diffusion is fast enough to dynamically update the information among all the participating members, so users do not need to get closer to fixed spots for receiving updated information.

***Index Terms*—5G mobile communication, Analytical models, Opportunistic networks, Contact-based Messaging, Performance Evaluation,**

I. Introduction

The growing share of people using mobile devices, offers the opportunity to build a ubiquitous infrastructure for electronic word-of-mouth messaging and advertising, making it especially suitable, for example, for a new form of viral marketing. Solely considering the use of fixed infrastructure-based solutions, e.g. 3G/4G or WiFi hotspots, entails important drawbacks like service or deployment costs, reduced coverage and performance when a given site is crowded, or due to the impact on propagation of modern building materials and structures. As a consequence, providers may try to reduce the quantity and quality of the content sent, minimising the diffusion of multimedia content, and thus reducing even more the number of users interested in being contacted.

E. Hernández-Orallo, J-C. Cano, C.T. Calafate and P. Manzoni are with the Departamento de Informática de Sistemas y Computadores. Universitat Politècnica de València. Spain.

M.Murillo-Arcila is with the Institut de Matemàtiques i Aplicacions de Castelló (IMAC), . Universitat Jaume I. Castelló, Spain.

J.A.Conejero is with the Instituto Universitario de Matemática Pura y Aplicada. Universitat Politècnica de València. Spain.

5G planning has a higher capacity than current 4G, allowing a higher density of mobile broadband users, and supporting device-to-device, ultra reliable, and massive machine communications. As an example of this short-distance high-speed wireless technology, the 802.11ad wireless standard (also known as WiGig) has been recently approved. WiGig is a short-distance WiFi standard that supports speeds of up to 4.6Gbps [1]–[3]. Opportunistic networks are an evolution of MANETs (Mobile Ad hoc Networks) and DTN (Delay-Tolerant Networks) systems that exploit human contacts for data sharing purposes. Instead of relying on a fixed infrastructure, the communication in mobile opportunistic networks takes place upon the establishment of ephemeral contacts among mobile nodes using direct communication. Adopting short-distance high-speed communication augments the benefits of opportunistic contacts, supporting transfers of up to 1GB of information in 5-10 seconds, and reducing network congestion and interferences.

In this paper we focus on the problem of distributing large amounts of data among visitors of open areas (shopping malls, museums, parks, etc.) through their mobile devices. We propose the combination of peer-to-peer opportunistic diffusion and short-distance high-speed wireless communication to achieve a faster dissemination. This model provides an extension to the one presented in [4], where only the transmission between mobile devices, and not fixed nodes was considered. Moreover, in this model the waiting time is also included.

In this work we assume a scenario where the information to be shared is stored (and kept updated) at various fixed spots, from where users can access simply by getting close to any of them. The type of content we are referring to is multimedia information like commercial videos about the shops and restaurants in the mall, or brief documentaries regarding the pieces of art in a museum. Since this information is also disseminated using opportunistic contacts between mobile devices, we avoid the necessity for all of them to move close to some of the fixed spots. Thus, our goal is to analytically study the performance of these opportunistic contact-based messaging scenarios.

The key contributions of our work are the following:

- We propose an analytical model based on *Population Processes* to understand the fundamental trade-offs of the information diffusion performance based on several parameters such as user density, contact rate, etc. We obtain closed-form expressions for the information diffusion time, network coverage, and waiting time. We also study their stable equilibrium points and their conditions. The performed evaluations show that these models correctly reproduce the dynamics of information diffusion.

- We show that, when user density is high, the diffusion is mainly dependant on opportunistic contacts among mobile nodes, and the coverage achieved is close to 100%. Regarding the arrival and departure of users, their impact is more important when user density is low.
- In our scenario, the diffusion is fast enough to dynamically update the information among all the participating members, so users do not need to get close to fixed spots for receiving updated information. Based on the closed-form expressions of the model, we can determine the frequency of information updating, showing that it mainly depends on user density and user renewal rate.

We consider that the results presented in this paper can be useful for the practical deployment of fixed nodes in open places, determining the practical coverage and diffusion time, as shown in the wide set of examples presented in the evaluation section for theme parks, commercial malls and museums.

The paper is organised as follows. After reviewing related work in Section II, we outline the diffusion scenario in Section III. In Section IV we introduce the performance models, and in Section V we present the evaluation of the selected scenarios using our model. Finally, in Section VI we conclude the paper.

II. Related work

It is well known that mobility affects the diffusion of messages in wireless networks [5]–[7]. Concretely, there have been several studies addressing the diffusion of information using opportunistic networks. The majority of these studies are focused solely on content diffusion among mobile devices. Zhang et al. [8] developed an analytical model to study epidemic content delivery. Other proposals such as [9], [10] evaluate the message dissemination behaviour of the Epidemic protocol by focusing on mobility patterns of the nodes. In these papers, the authors explain the relationship between factors such as speed, mobility model, node density, and places. Some papers are more focused on evaluating the impact of human behaviour in the opportunistic forwarding of messages [11], [12].

In order to improve connectivity in mobile networks, several papers have proposed adding fixed infrastructures such as base stations, relays or meshes, known as hybrid networks [13]. Another approach, such as placing a sparse set of well-connected base stations in an ad hoc wireless network has been studied in [14]. In [15], the authors analysed whether the use of autonomous agents can improve the performance of sparse mobile networks, while in [16] it was studied how systems of base stations, called *Infostations*, are able to provide intermittent coverage and connectivity in mobile networks.

Some other papers studied how to offload the wireless infrastructure through opportunistic communications. Hui et al. [17], evaluate how these hybrid networks can improve message delivery ratios. More concretely, they conclude that opportunistic communication improves the system capacity and delay, even with infrastructure networks with high access point density. Some other papers are more focused on offloading the cellular networks load. Whitbeck et al. [18], evaluate a context dissemination framework (Push-and-track) to minimise the load on the cellular network infrastructure while guaranteeing tight delivery delays. Lee et al. [19], present a study of the real performance of 3G mobile data offloading through WiFi networks, showing a reduction of 65% 3G traffic . Han et al. [20] investigate several strategies to find the subset of opportunistic users that will lead to the greatest infection ratio by the end of a message's lifetime, in order to minimise the load on the infrastructure. A recent paper by Sciancalepore et al. [21], proposes HYPE (HYbrid oPportunistic and cEllular), a technique which minimises the load on the cellular network while meeting delay constraints. A similar approach, TOSS (Traffic Offloading by SNS-Based opportunistic sharing) is introduced in [22]. In general, these papers focus on reducing the network load, but no evaluation is performed to determine the impact of user density on the opportunistic diffusion process.

A related approach is the so-called Floating Content [23]. Floating content is a contact sharing application, where a message at a certain area is tagged with geographical coordinates of that area, that is referred to as the anchor-zone of the message. This approach is a kind of best effort service, in which messages are locally generated, their availability is geographically limited and their lifetime and diffusion depend on the mobility and resources of mobility nodes. Recently, this approach has been evaluated in open city squares in [24] using a custom mobility model, spatial analysis and Markov chains, and assuming that nodes enter and leave the city square.

Some other papers study in detail the mobility of pedestrians in realistic spaces, such as buildings and streets, and evaluate its impact on message diffusion performance. For example, the authors in [25] study the mobility along a street using a pedestrian mobility simulator (LEGION) which is usually considered in urban and traffic planning. Based on these results they develop an analytical model to study the connectivity properties. A more detailed study using the same mobility simulator was performed by Helgason et al. [26]. Concretely, they evaluated the impact of mobility in two simulated scenarios on opportunistic communication (mainly inter-contact time and contact duration). They also evaluated the impact of access points (AP) location on this opportunistic communication. The results show that, as expected, the type of scenario is the most import aspect to consider. Coupling a mobility simulator, such as SUMO, with a diffusion simulator is a very common approach for evaluating the diffusion of VANETs [27].

Another study by Pajevic et al. [28] proposes a model based on SDE (Stochastic Differential Equations) for crowd-counting using an application that receives messages from AP (access points) and by contact between mobile nodes using the scenarios from [26]. Although the previous models, can capture some of the *microscopic* dynamics of pedestrian mobility and interactions, they are very specific to the simulated scenario, and their applicability to other scenarios is not clear. A similar approach to ours, but using low-speed transmission, is the one presented by Vukadinovic et al. [29]. They performed an experimental evaluation based on the mobility of visitors in an entertainment theme park in order to understand network requirements (minimum number and density of mobile devices and supporting infrastructure nodes) for opportunistic communication. Being just an experimental testbed, no performance model is obtained. The results show that, in this scenario, the efficiency of the diffusion depends on user density and the distribution of contacts. Some of the results presented in [29] match the ones obtained in our paper, validating our model empirically.

A common approach regarding the performance evaluation of message diffusion, as detailed previously, is to combine a network simulation tool with realistic mobility traces or mobility simulators. Although these evaluation approaches can provide realistic results, the key mechanisms underlying the information diffusion are difficult to identify because of the amount of details integrated in these models. Furthermore, simulation can be very time consuming, and has to be restricted to the scenarios for which mobility traces are available or generated. In such cases, analytical models can avoid these drawbacks by providing a faster and broader performance evaluation, being fundamental to the systematic investigation of the impact of the complex features of information diffusion. Two types of analytical models have been proposed for modelling this type of network dynamics: Markovian models [22], [30]–[35], and deterministic models based on Ordinary Differential Equations (ODEs) [8], [13], [31], [36], [37]. The main problem with Markov chain models is that, if no closed-form expressions are obtained, their numerical resolution when the number of nodes is high is unfeasible, and so they cannot be used to model crowded places. In general, as the population size N becomes large, ODEs can be derived as the limits of Markovian models, as it was stated by the Kurtz's convergence theorem [38].

We based our model on *Population Processes*, a method commonly used to model the dynamics of biological population [39]. Haas and Small [31] presented a model based on epidemiological processes for a network that used animals (whales) as data carriers to store and transfer messages (a similar approach to DTN). Zhang et al. [8] derived ODE equations for studying the dynamics of various forwarding and recovery DTN schemes, such as epidemic and 2-hop, among others. Banerjee et al. [13] introduced an ODE for evaluating hybrid networks with fixed nodes. The authors of [36] introduced a mathematical approach for describing messages diffusion in opportunistic networks using the Epidemic protocol. This approach is based on well-known models for the spreading of human epidemical diseases, e.g. SIR (Susceptible, Infectious and Recovered) models. One of the main conclusions of their analysis (mathematical model and its respective simulation) is that SIR models are quite accurate for the average behaviour of Epidemical DTN. In [37] the authors proposed a detailed analytical model to analyse the epidemic information dissemination in mobile social networks. It is also based on SIR models including rules that concern user's behaviour, especially when their interests change according to the information type, and it can have a considerable impact

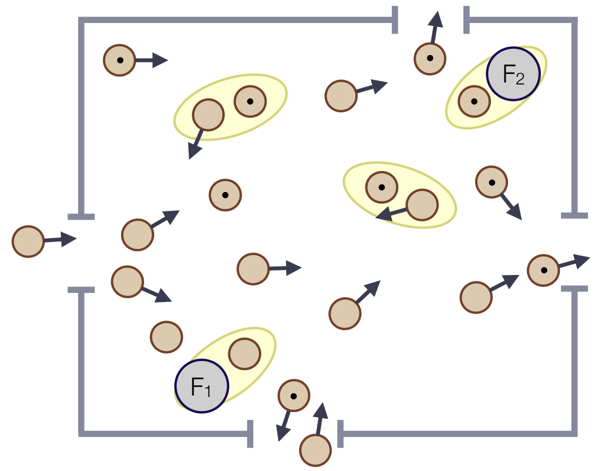


Fig. 1: A sample scenario: a place with two fixed spots and several mobile nodes. Mobile modes can receive the information from the fixed nodes (F_1 and F_2) or from other nodes (if one of the nodes has the information).

on the dissemination process. Nevertheless, these previous models, do not take into account several social aspects that influence the performance of message dissemination, such as the user density, and the dynamics of users arriving and leaving a place.

III. Diffusion scenario

The scenario studied in this paper is an open area where users can enter and leave (e.g., a public square, a shopping mall, live concerts, etc.). Relevant information regarding the place has to be disseminated (and kept updated) rapidly among the present users (see figure **??**). Beside typical textual and photographic information, we particularly consider multimedia content, such as commercial videos in shopping malls, video guides in touristic places, music videos in live concerts, etc, meaning that the size of the information transferred can be very high (about 1GB). This information is expected to be stored in fixed nodes deployed throughout the place and delivered to the mobile devices of users either directly or indirectly.

Direct delivery refers to users accessing content by simply getting close to any of the fixed spots. *Indirect delivery* is performed using contact-based communication by establishing direct short-range links directly between mobile devices. The delivered content is stored in these devices to enable its distribution when future contacts take place achieving a full dissemination of this content.

We will use short-distance high-speed communication links because they allow augmenting the benefits of opportunistic contacts since, even for short-lived connections lasting 5-10 seconds, we can transfer approximately 1GB of information. We therefore consider that, at these speeds, when a contact occurs the nodes can exchange all the information stored in their buffers.

Information dissemination takes place as follows: users have mobile devices with a custom application that notifies and shows the user the received information. Each mobile node has a local buffer where all the information is stored. The mobile contact-based diffusion occurs when two nodes establish a pair-wise connection, so that nodes having updated information may transmit it to the others. Contact-based information spreading is based on epidemic diffusion, a concept similar to the spreading of infectious diseases, where an infected node (the one that has the information) contacts another node to infect it (transmits the information). Epidemic routing obtains the minimum delivery delay at the expense of increased buffer usage and increased number of transmissions[1]. All nodes running the application collaborate in storing and forwarding the information. Regarding the fixed nodes, there is a set of F *visible* spots distributed throughout the place. The user can also move close to a fixed spot and stay there for several seconds in order to receive the updated information. Summing up, both kinds of communication are based on contacts using short-range high-speed transmission.

Typically, not all contacts will end with a successful transmission. The effectiveness of a transmission depends on several factors, mainly contact duration, but also on interferences and social behaviours such as selfish nodes. We define an *effective contact* as the contact that is successful, i.e., whose duration allows the complete transfer of all the desired information. Assuming a contact rate $\hat{\lambda}$ that comprises all opportunistic contacts between pairs of nodes, and defining p as the probability of successful transmission, the *effective contact rate* is simply $\lambda = p\hat{\lambda}$. Thus, from now on, we will use the term *contact rate* to refer to the *effective contact rate*, that is a composite measure of contact rates and transmission probability.

Regarding information updating, our goal is to avoid that users need to return to the fixed spots. Thus, when new or updated information is generated, it is transmitted to the fixed nodes, so that these nodes start the diffusion of this updated information. Then, a new diffusion is started, and the nodes that have the updated information transmit it whenever a new contact takes place. The update frequency will depend on the final diffusion time. As shown later in this paper, this time is short (in the order of minutes). Finally, we devise two ways of deleting this information; the first one is a simple expiration time approach based on the TTL of the information, and the second one occurs when the user leaves the place through location-based services.

IV. Performance model

In this section we propose an analytical performance model to evaluate the dissemination of information in the scenario described in the previous section. This performance model is based on *population processes or models*. A population model is a mathematical model used in population dynamics to model the spread of parasites, viruses, and diseases [39]. Specifically, our model is based on *biological* epidemic models [40], where individuals can be infected by other nodes when a contact occurs. In our case, an infected node refers to a node that has the information, and an infection refers to the process whereby a node that has the information transmits it to another node. First, we will introduce the basic epidemic model, that is then extended to an open place with fixed nodes. This deterministic approach relies on the homogeneous mixing approximation, which assumes that the individuals in the population are well mixed and interact with each other completely randomly.

A. Basic epidemic model

In the basic epidemic model [8], nodes move freely within a closed area with a given effective contact rate between pairs λ. The number of nodes N in a place remains constant, and when a node carrying information (an *infected* node) contacts another node that does not have the updated information (called the *susceptible* node), they immediately exchange the information. From that moment on, both nodes carry the same information. The dynamics of this system can be expressed using a deterministic model based on ODE's (Ordinary Differential Equations):

$$\begin{aligned} S'(t) &= -\lambda S(t)I(t) \\ I'(t) &= \lambda S(t)I(t) \end{aligned} \tag{1}$$

for all $t \geq 0$, where $I(t)$ denotes the class of infected nodes at time t, $S(t)$ refers to the class of susceptible nodes to be infected, and $\lambda > 0$ stands for the growth rate where the number of infected nodes increases proportionally to the number of infected and non-infected ones. The population remains constant: $N = I + S$. These ODE's have an analytical solution assuming one initial node infected ($I(0) = 1$) [8]. More specifically, the infected nodes are described by the logistic function:

$$I(t) = \frac{N}{1 + (N-1)e^{-\lambda N t}} \quad \text{for all } t \geq 0. \tag{2}$$

B. Open place with fixed nodes model

In this subsection we propose a new model for evaluating the diffusion of information in the scenario described in section III. Specifically, nodes move freely within a given area with a contact rate between pairs $\lambda > 0$, and new nodes come to the place with an *arrival rate* $\beta > 0$. New nodes are susceptible nodes (that is, they do not have the information yet). We suppose that nodes leave the place with an *exit rate* $\delta > 0$. These parameters correspond to the birth and death rates of the epidemical models. Thus, the number of nodes (population) in the place at time t, $N(t)$, depends on the initial number of nodes in the place, $N_0 = N(0)$, and also on the arrival and exit rates. We assume a short-range communication scope, so network congestion and interferences do not have a strong impact on performance.

In our model, we consider that both susceptible and infected nodes can leave the area. This behaviour differs from the typical death rate of epidemic SIR models, where only the infected nodes can be removed due to death (that is, *leave* the place). Therefore, the final exit rate for each of these classes of susceptible and infected nodes is proportional to the relative number of nodes in each of them. Thus, the number of nodes is not constant over time, and it can be obtained as

[1]Note that our goal is to perform a full diffusion of the information, so epidemic routing is the best choice. Other routing strategies have been proposed for point-to-point transmission, such as two-hop, PRoPHET, spray and wait, etc. to reduce the network load.

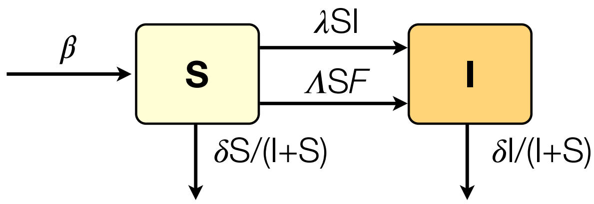


Fig. 2: Graphical representation of the transitions between classes.

$N(t) = N_0 + (\beta - \delta)t$, where $N(t) = I(t) + S(t)$, assuming also that $N(t) > 0$ for all $t \geq 0$.

Let us assume that in the place there are F fixed nodes, with an effective contact rate $\Lambda > 0$ among mobiles nodes and fixed nodes[2]. When a contact between a fixed node and a susceptible mobile node occurs, the mobile node gets infected (that is, it receives the information). We always assume that only susceptible nodes contact with fixed nodes, as infected nodes already have the information.

To design our model we take into account the following transitions (see figure 2):

- $(\rightarrow S, \beta)$: new nodes enter the place with arrival rate β.
- $(S \rightarrow I, \lambda SI)$: new nodes get the information when effective contacts between mobile nodes occurs.
- $(S \rightarrow I, \Lambda SF)$: new nodes receive the information from fixed nodes.
- $(S \rightarrow, \delta S/(I+S))$: nodes with no information leave the place.
- $(I \rightarrow, \delta I/(I+S))$: nodes with the information leave the place.

This system can be expressed using a deterministic model based on ODE's:

$$\begin{aligned} S'(t) &= -\lambda S(t)I(t) + \beta - \delta S(t)/N(t) - \Lambda S(t)F \\ I'(t) &= \lambda S(t)I(t) - \delta I(t)/N(t) + \Lambda S(t)F \\ N'(t) &= \beta - \delta \end{aligned} \tag{3}$$

C. Dynamics of the model

Now, we are going to study the dynamics of this system. First, we focus our evaluation on the number of nodes, that will depend on the arrival and exit rates. Figure 3 shows the evolution of the infected nodes $I(t)$ and the overall number of nodes $N(t)$ as a function of time for different arrival and exit rates. All plots start with the same number of nodes ($N_0 = 100$ and $F = 2$), zero infected nodes ($I(0) = 0$), and contact rates $\lambda = \Lambda = 0.001$. Three posible cases are evaluated: the first one is when $\beta < \delta$, and, as shown in Figure 3a, all the nodes leave the place, making $N(t)$ fall to 0. Figure 3b shows the case when $\beta > \delta$ where the number of nodes increases indefinitely[3]. Finally, in Figure 3c, we study the case when $\beta = \delta$. First, we see that, when there are no arrival and exits ($\beta = \delta = 0$), the system reaches an equilibrium point where all nodes get the information. However, when the system has the same arrival and exit rate (for example, $\beta = \delta = 1$) the system reaches an equilibrium point, but not all the nodes get the information ($I(t) < N(t)$). This is the most relevant case, and we proceed to study the equations in (3), when the system reaches the equilibrium, that is, $N(t) = N_0$ and $\beta = \delta$. In this case, if we consider the $I'(t)$ equation from (3), and replace $N(t)$ with N_0, and $S(t)$ with $N_0 - I(t)$, we have:

$$\begin{aligned} I'(t) &= \lambda(N_0 - I(t))I(t) - \beta I(t)/N_0 + \Lambda(N_0 - I(t))F \\ &= -\lambda I^2(t) + \left(\lambda N_0 - \Lambda F - \frac{\beta}{N_0}\right) I(t) + \Lambda N_0 F \end{aligned} \tag{4}$$

which is a Riccati differential equation. To simplify the notation we denote $b = \lambda N_0 - \Lambda F - \frac{\beta}{N_0}$. The general solution of (4) will be given by $I(t) = I_p(t) + \frac{1}{z(t)}$, where I_p denotes a particular solution of (4) defined as:

$$I_p(t) = \frac{b - \sqrt{b^2 + 4\lambda\Lambda N_0 F}}{2\lambda}, \quad \text{for all } t \geq 0. \tag{5}$$

On the other hand, $z(t)$ denotes the solution of the linear differential equation $z'(t) = (2\lambda I_p - b)z(t) + \lambda$. Solving this equation, and considering the initial condition $I(0) = 0$, we obtain:

$$I(t) = I_p + \frac{1}{Ce^{dt} - \frac{\lambda}{d}}, \quad \text{for all } t \geq 0, \tag{6}$$

with $d = 2\lambda I_p - b$, and $C = \frac{\lambda I_p - d}{dI_p}$.

Using this equation we can obtain the diffusion time T_d for M nodes setting $I(t) = M$ and solving for t:

$$T_d(M) = \frac{1}{d} \log\left(-\frac{d - I_p\lambda + \lambda M}{CdI_p - CdM}\right) \tag{7}$$

Now, from equation (4), we are going to find the equilibrium points (S_e, I_e) of the discrete unidimensional system obtained when taking into account that, in the equilibrium $\beta = \delta$ and $I(t) + S(t) = N_0$. For studying the equilibrium points, we derive a discretised equation of $I(t)$ for $h > 0$ small enough:

$$I_{i+1} = I_i + h(-\lambda I_i(N_0 - I_i) - \beta I_i/N_0 + \Lambda(N_0 - I_i)F) \tag{8}$$

The equilibrium points are given as solutions of

$$-\lambda I^2 + (\lambda N_0 - \frac{\beta}{N_0} - \Lambda F)I + \Lambda N_0 F = 0. \tag{9}$$

To simplify the notation let $b = (\lambda N_0 - \frac{\beta}{N_0} - \Lambda F)$, and solving the quadratic equation we have:

$$I = \frac{-b \pm \sqrt{b^2 + 4\lambda\Lambda N_0 F}}{-2\lambda}. \tag{10}$$

Since in our model the number of infected nodes must be always positive, the unique equilibrium point is given by $I_e = \frac{b + \sqrt{b^2 + 4\lambda\Lambda N_0 F}}{2\lambda}$. Let

$$f(I) = I + h\left(-\lambda I^2 + (\lambda N_0 - \frac{\beta}{N_0} - \Lambda F)I + \Lambda N_0 F\right).$$

[2]Note that both λ and Λ refers to the average contact rate between pairs of nodes and not between all nodes, so these contact rates do not depend on nodes density

[3]To be realistic, we can impose a limit L to the number of nodes in the place (the capacity of the place), so when $N(t) \geq L$, β is set to δ (that is, the entrance is restricted).

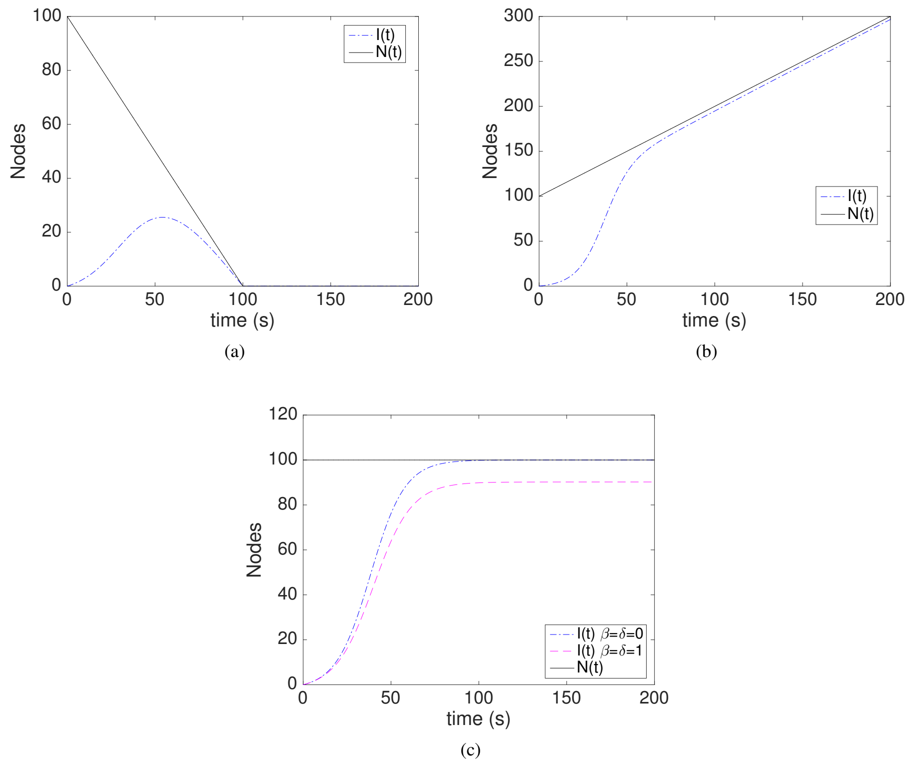


Fig. 3: Evolution of the infected nodes for different values of β and δ. We used for all plots $\lambda = \Lambda = 0.001$, $N_0 = 100$ and $F = 2$. For obtaining these plots, equations 3 are numerically solved using Euler's method, with a step size of $h = 0.001$. : a) $\beta = 0$, $\delta = 1$ b) $\beta = 1$, $\delta = 0$; c) $\beta = \delta$ for 0 and 1.

Finally, we analyse the behaviour of I_e. The derivative of f is given by $f'(S) = 1 + h\left(-2\lambda I + \lambda N_0 - \frac{\beta}{N_0} - \Lambda F\right) = 1 + h\left(-2\lambda I + b\right)$. Since, $f'(I_e) = 1 - h(b + \sqrt{b^2 + 4\lambda\Lambda N_0 F})$, we get $|f'(I_e)| < 1$, and then I_e is an attractor.

Due to the fact that $S(t) + I(t) = N_0$ for all $t \geq 0$, we can directly extend these results to the two-dimensional case. As a consequence, the only equilibrium point that will exist is the one obtained from I_e, that is:

$$(S_e, I_e) = \left(\frac{v - \sqrt{b^2 + 4\lambda\Lambda N_0 F}}{2\lambda}, \frac{b + \sqrt{b^2 + 4\lambda\Lambda N_0 F}}{2\lambda}\right) \tag{11}$$

where $b = \lambda N_0 - \Lambda F - \frac{\beta}{N_0}$ and $v = \lambda N_0 + \Lambda F + \frac{\beta}{N_0}$. It is important to remark that this point will always make sense since $S_e, I_e \geq 0$ for all $\lambda, \beta, \Lambda, F$.

Now, we study the influence of the two classes of contacts, that is, between pairs of nodes, and between mobile nodes and fixed nodes. The mean number of contacts per second between all pairs of nodes is $\lambda N(N-1)$. In a similar way, for the fixed nodes, this number is $\Lambda N F$. If the number of nodes N and the contact rates λ, Λ are constant, an increase in the number of fixed nodes F causes an increase of the number of contacts of this type. In Figure 4 we plot the evolution of the infected nodes $I(t)$ assuming that the diffusion is performed only by *indirect delivery*, that is, only through contacts between mobile nodes[4], so $\Lambda = 0$; and finally, assuming that diffusion is performed by *direct delivery*, that is, only through contacts with the fixed nodes, so $\lambda = 0$. All plots start with the same number of nodes $N_0 = 100$, the same arrival and exit rates $\beta = \delta = 1$, and the same contact rates $\lambda = \Lambda = 0.001$. Note that we are interested in the relation between the two classes of contacts. In the first plot (Figure 4a) we assume a reduced number of contacts between the fixed nodes by setting $F = 2$. We can clearly observe that diffusion is mainly performed by the mobile contacts, since the impact of the fixed nodes diffusion is very reduced (it only reaches 20 nodes). The second plot (Figure 4b) shows the results of increasing the number of fixed nodes contacts with $F = 20$. We can see that both classes of diffusion have a similar contribution to the diffusion process as a whole. Finally, in Figure 4c, we set $F = 100$, and in this case the diffusion is mainly performed by the fixed nodes.

[4]Note that, in this case we assume that only one node has the information at the beginning, that is $N_0 = 1$

D. Waiting time

The previous expressions (mainly diffusion time and infected nodes) evaluate the performance of the whole system. Nevertheless, it is interesting to evaluate this performance from the user's point of view. That is, when a person enters the place, how long does it take to receive the information? This delay is known as the *waiting time*. In this case, we assume that the system has reached the equilibrium, and so the number of nodes with the information is I_e, and users do not leave the place until they receive the information. So, this new node will receive the information when it contacts with an infected

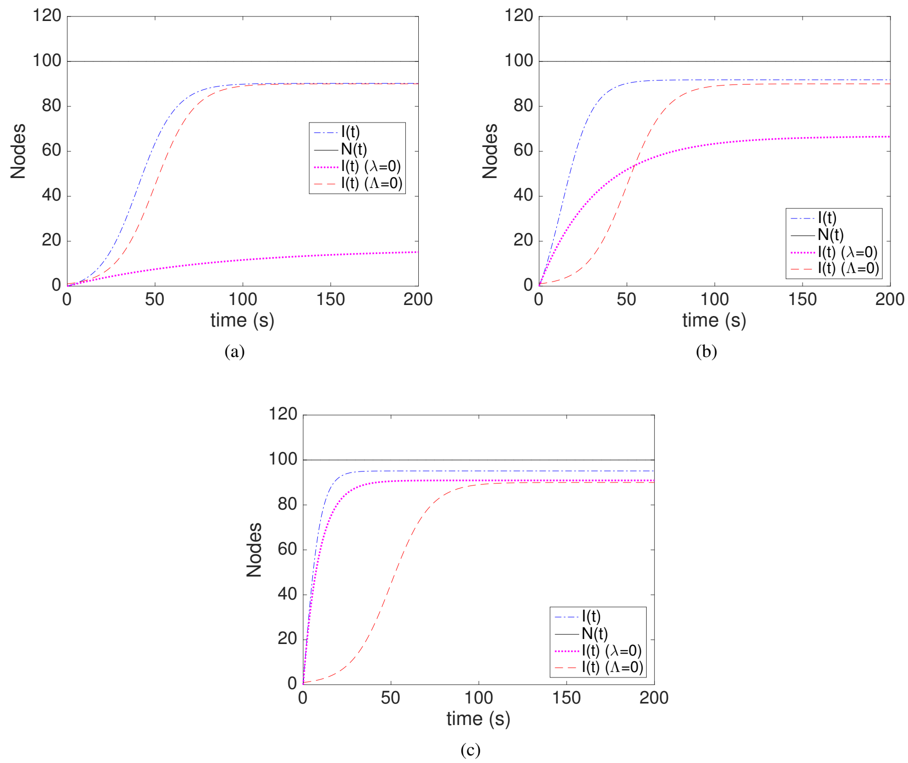


Fig. 4: Evolution of the infected nodes for different values of λ and (Λ, F). We used for all plots $\beta = \delta = 1$, $\lambda = \Lambda = 0.001$ and $N_0 = 100$. For obtaining these plots, equations 3 are numerically solved using Euler's method, with a step size of $h = 0.001$. a) Low number of fixed nodes: $F = 2$ b) Medium number of fixed nodes $F = 20$; c) High number of fixed nodes: $F = 100$.

node or a fixed node with rates λ or Λ, respectively. This can be expressed as a pure birth process, with two states: $k = 0$, representing that no information is received, and $k = 1$, if the information is received. The birth rate $\lambda_b = \lambda I_e + \Lambda F$ is constant, meaning that we have the familiar Poisson process, and so the arrival time for $k = 1$ is the expected waiting time:

$$T_w = E[T_1] = \frac{1}{\lambda_b} = \frac{1}{\lambda I_e + \Lambda F} \tag{12}$$

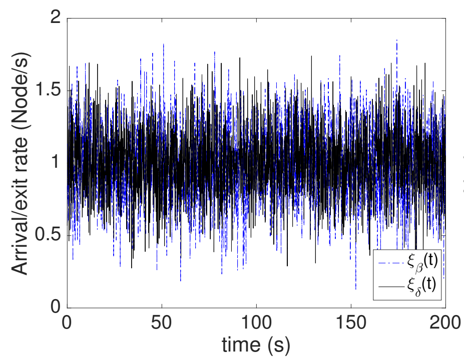
when the system gets an equilibrium point.

E. Impact of variability in the arrival/exit rates

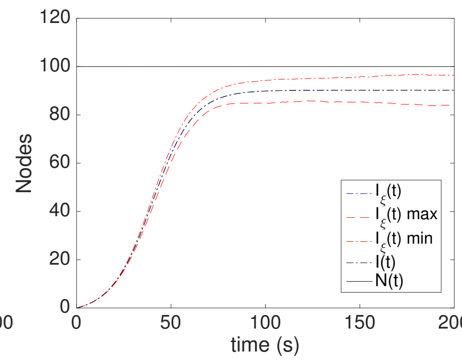
Imposing the equilibrium condition for the analysis of real scenarios could be a very strong requirement, especially when the arrival and exit rates vary along the time, considering that sometimes there are more people arriving than exiting (and vice-versa). Although in the previous deterministic model we are taking mean values of these rates, now we are going to evaluate how the variation of these rates can impact on the equilibrium and thus on the previous expressions. For this study, we are going to incorporate noise for β and δ parameters in the ODE's of the dynamic model. This approach is a way to evaluate the dynamics of a diffusion system that are subjected to some random variability and this variability is propagated forward by the underlying equations [41]. For the arrival rate, let $\xi_\beta(t)$ be a time series representing the noise derived from a normal distribution with mean $\mu = \beta$ and variance σ^2 (for the exit rate we derive also $\xi_\delta(t)$). Then, equations in (3) are transformed to:

$$\begin{aligned} S'_\xi(t) &= -\lambda S_\xi(t) I_\xi(t) + \xi_\beta(t) - \xi_\delta(t) S_\xi(t)/N_\xi(t) - \Lambda S_\xi(t) F \\ I'_\xi(t) &= \lambda S_\xi(t) I_\xi(t) - \xi_\delta I_\xi(t)/N_\xi(t) + \Lambda S_\xi(t) F \\ N'_\xi(t) &= \xi_\beta(t) - \xi_\delta(t) \end{aligned} \tag{13}$$

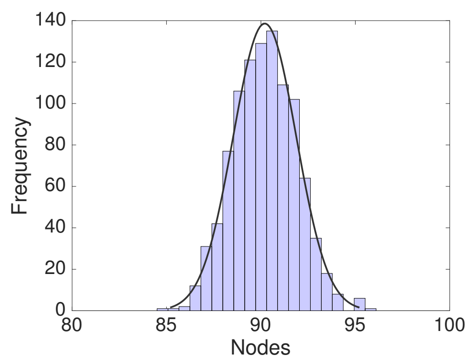
Note that no equilibrium can be reached from this system, due to the continuous variation of the arrival and exits rate. Nevertheless, it can reach a *quasi-stationary* equilibrium so we can evaluate the impact that the arrival/exit variation has on the infected nodes. We used the same parameters as in previous experiments ($\lambda = \Lambda = 0.001$, $N_0 = 100$ and $F = 2$), with the arrival and exit rates following a normal distribution for $\beta = 1$ and $\sigma = 0.25$, as shown in figure 5a. We obtained 1000 different realisations of $I_\xi(t)$ resolving equations (13) using Euler's method. The results for the mean, maximal and minimal values of $I_\xi(t)$ are shown in 5b. We can see that the mean, as expected, coincides with the deterministic resolution of $I(t)$, and than the variation from this mean is very low. Furthermore, we can see that the number of infected nodes at time 200s (that is, when the deterministic model is in equilibrium), also follows a normal distribution, with $\mu = 90$ and $\sigma = 1.67$, showing a low standard deviation. This fact confirms, that the deterministic model is a good approximation even with varying arrival and exit rates.



(a)



(b)



(c)

Fig. 5: Evaluation of the impact of the variation of the arrival/exit rates. We used for all plots $\lambda = \Lambda = 0.001$, $N_0 = 100$ and $F = 2$. For obtaining these plots, equations 13 are numerically solved using Euler's method, with a step size of $h = 0.001$. a) A sample of the arrival/exit rate with $\xi_\beta(t)$ and $\xi_\delta(t)$ following a normal distribution $\mathcal{N}(1, 0.25^2)$. b) Evolution of the infected nodes depending on time; c) Distribution of $I_\xi(200)$, showing a Normal fit.

V. Performance evaluation

The model introduced in section IV allows us to evaluate the dynamics of the information diffusion in a place and to calculate parameters such as the number of nodes having the information, the diffusion time, and the waiting time when the system reaches the equilibrium. Since the evolution and dynamics of the system were already studied in section IV, in this section we focus on scenarios where the system reaches an equilibrium state, that is, assuming that the arrival and exit rates are the same. From now on, we refer to both rates jointly as the renewal rate. First, we consider a generic evaluation, where we evaluate the performance depending on user density, renewal rate, contact rate, and number of fixed nodes. Next, we apply the model to the study of several real scenarios.

A. Generic evaluation

In this subsection we consider a place with an area of about $A = 10.000m^2$ with N_0 mobiles nodes (i.e. users) and a *user density*[5] $d = N_0/A$. Based on the studies provided in [42], user density in open places for walking profiles can range from 0.005 to 0.2 users per square metre (u/m^2). With these densities, users can move freely, entering and leaving the place with a renewal rate $\beta = \delta$, carrying a mobile device that can establish pair-to-pair connection using short-distance high-speed connections. Instead of directly using the renewal rate, for practical purposes, we use the *(relative) renewal percentage* (RR), defined as the percentage of nodes that are renewed in the place every second: $RR = 100 \cdot \beta/N_0$. Based also on [42], typical values of RR range from 0 (no renewal) to 1% (fast renewal)[6].

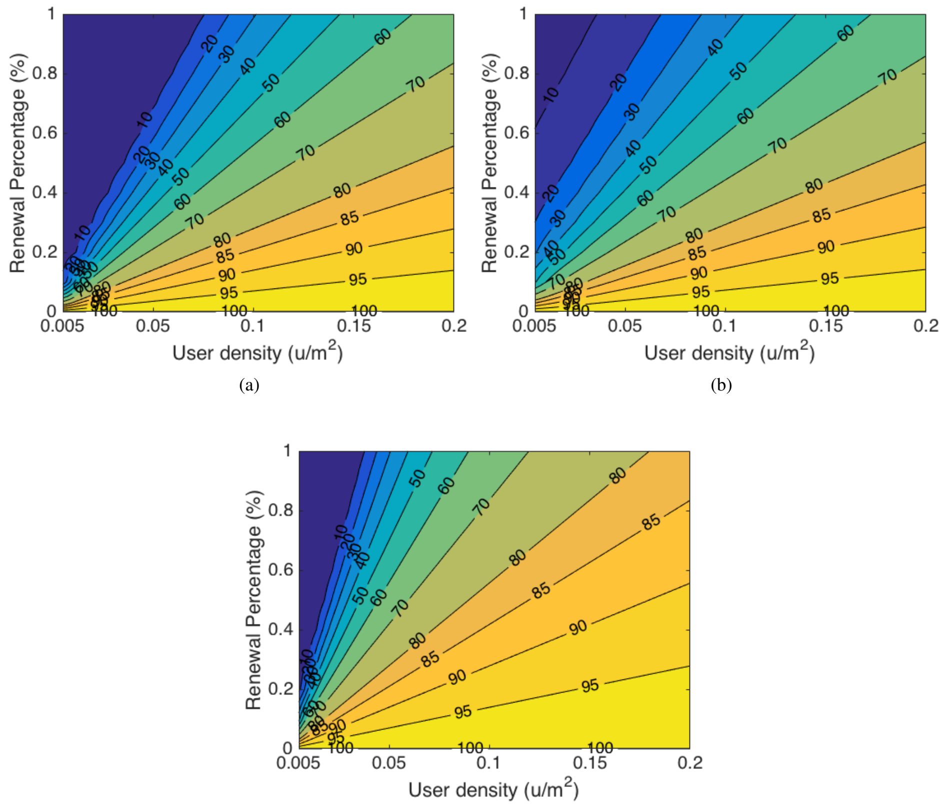
Regarding the contact rate between pairs of mobile nodes, empirical results on the inter-meeting time via real, extensive mobility traces [43]–[46], show that the contact rate λ ranges between 0.1 and $0.01c/h$ [7]. For the contact rate between mobile nodes and fixed nodes, we use $\Lambda = 0.11c/h$, that was experimentally obtained in [47]. Note that the impact of the fixed nodes will depend on both the contact rate and its number (factor ΛF), and so we set the contact rate to $\Lambda = 0.11c/h$, and we vary the number of fixed nodes in order to increase the diffusion performance.

We first evaluate the *diffusion coverage*. We define *diffusion coverage* as the final percentage of users that receive the information when the system reaches the equilibrium. This value is obtained evaluating the factor $100 \cdot I_e/N_0$ using expression (11). This coverage is represented using a contour

[5]Note that we are only considering as users the people willing to receive the information and to collaborate in the diffusion, which may be only portion of all the people in the place. When real values are used we consider half of the people as communicating nodes.

[6]Note that 1% is an extremely high renewal rate, since it implies that in 100s all users are renewed. As an example we have a subway walkway.

[7]From now on, we express the contact rate as contacts per hour.



(a)

(b)

(c)

Fig. 6: Diffusion coverage depending on user density and renewal percentages. a) with $F = 2$ and $\lambda = 0.05c/h$; b) increasing the number of fixed nodes to $F = 20$ with $\lambda = 0.05c/h$; c) with a higher contact rate $\lambda = 0.1c/h$ and $F = 2$;

plot depending on user density and renewal percentage. Figure 6a is the coverage plot with two fixed nodes ($F = 2$) and contact rate $0.05c/h$. We can see that when density increases, the percentage of users receiving the information also increases, reaching nearly 100% of the users when density is very high, and the renewal percentage is below 0.1. This diffusion is mainly dependant on inter-mobile contacts. For low densities and higher renewal percentages, the achieved coverage is reduced to values below 50% of the users. If we increase the number of fixed nodes ($F = 20$) the coverage is increased, as shown in Figure 6b. We observe the impact that fixed nodes have on the diffusion process when population density is low. We also see that these fixed nodes increase the diffusion coverage by comparing these results with the ones obtained when considering only two fixed nodes (Figure 6a). Nevertheless, this contribution to the diffusion process is vanished when user density increases. Finally, if the contact rate is higher ($\lambda = 0.1c/h$), we can see in Figure 6c that the achieved coverage increases for all densities and renewal percentages. Summing up, increasing the number of fixed nodes can improve the coverage when the user density is low, but the diffusion mainly depends on *indirect deliveries* (that is, between mobile nodes), a fact that becomes more evident when the contact rate is increased.

We now evaluate the diffusion time of the information using expression (7). Figure 7 shows the diffusion time depending

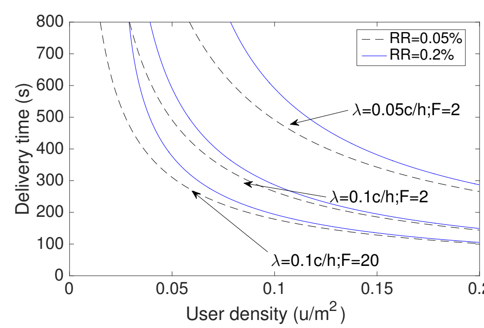
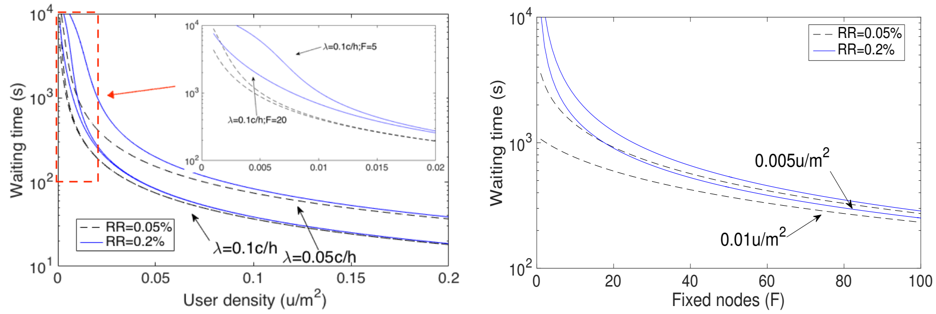


Fig. 7: Diffusion time depending on the user density for two different renewal rates (0.05% and 0.2%), with different values of fixed nodes and contact rates.

on user density for two renewal rates (0.05% and 0.2%), and for two amounts of fixed nodes ($F = 2$ and $F = 20$). Since reaching 100% of the nodes is not possible when the renewal rate is greater than zero, we plot the diffusion time for lower diffusion coverage ratios (75% to be more specific). In general, we can see that diffusion time decreases exponentially with user density. As expected, with a higher contact rate ($\lambda = 0.1$) the diffusion time is reduced, especially when user density is low. We can reduce this diffusion time by increasing the number of fixed nodes, as shown in the curves for $\lambda = 0.1$ and $F = 20$. Note, that when density is very low, the coverage is below 75%, and so the diffusion time is not represented.



(a) (b)

Fig. 8: Evaluation of the waiting time for receiving the information. a) depending on user density for two different renewal rates (0.05% and 0.2%) and number of fixed nodes 2 and 20; b) depending on the number of fixed nodes for $\lambda = 0.05c/h$; Note that the y-axes are in log scale.

Finally, it is also relevant to evaluate the *waiting time*, that is, the expected time a user who enters a place has to wait in order to receive the information, using expression (12). In Figure 8a we show the waiting time using the same parameters as in Figure 7. In general, we can see that, when user density is high, the waiting time is very low (less than 30 seconds) because it takes little time to contact another user carrying the information. For low densities, the effect of increasing the number of fixed nodes becomes quite evident as it can be seen in the plot zoom available in the graph. These cases deserve more scrutiny, and so Figure 8b shows the waiting time depending on the number of fixed nodes for low user densities, that is, $\lambda = 0.05c/h$. The results confirm that, for low densities, an increase in the number of fixed nodes has a great impact on the reduction of the waiting time.

The results of the previous evaluations reveal that the factor which has more impact on the effectiveness of the diffusion is user density. When the density is high, the diffusion is mainly performed by mobile nodes. Nevertheless, when the density is low, we can increase the coverage and reduce the waiting time by increasing the number of fixed nodes. The renewal rate also affects the coverage, reducing it when the renewal rate is higher. Finally, the contact rate is the main factor affecting the diffusion speed.

B. Case studies

In this subsection we study several real scenarios from a *macroscopic* perspective, thereby providing a glance of its performance under different situations. It is clear that density can vary along the different areas of a place and, if we want results with more resolution, we need to perform a *microscopic* evaluation, through simulation or experimental evaluation. Furthermore, the arrival and exits rates can also vary along time, but as shown in subsection IV-E, the deterministic model is a good approximation. The data about the user density and the entrance rate were collected from different sources as detailed below, and both the data scenario and the main results are shown in Table I.

Shopping mall: The data for this scenario was extracted from a fire risk analysis study of several shopping malls in Hong-Kong [48]. Specifically, we used the values from the Central & Western (Mall D) at two different hours: at 19:00, when the mall is crowded, and at 13:15, when the mall is near empty. For the contact rates, we used the experimental values obtained for mobile devices using Bluetooth in [47], that is, between mobile nodes ($\lambda = 0.06c/h$), and between mobiles nodes and fixed nodes ($\Lambda = 0.1c/h$). Finally, we consider 5 fixed nodes to be deployed in this mall. The results show that, when the shopping is crowded (0.15 u/m^2), the coverage is nearly 100% with a waiting time of 31s. Even when the shopping mall is near empty (0.01 u/m^2), the coverage is high (82%) with a reasonable waiting time (9 minutes). If we increase the number of fixed nodes ($F = 10$), we can see a reduction of the diffusion time, while the improvement in the coverage and waiting times is minimal due to the impact of the renewal rate on the low node density of the area.

Theme Park (Epcot park): In this scenario the data used is based on the figures presented by Vukadinovic et al. [29]. For the first evaluation (*second row of Park scenario* in table I), we assume the same conditions of their experiments, that is, only 5 to 8% of the visitors have mobile devices, considering only 800 mobile devices and one access point ($F = 1$). Note also that, although the park covers an area of $1.2km^2$, we assume that users can stand and walk only in the 20% of this area. We also consider that the renewal rate is low, because in parks the highest entrance/exit rates on the park occur at opening/closing times. First, the diffusion time closely resembles the results of the paper (that were approximately 600s for 75% of nodes). The coverage is very high, and the waiting time is about 90 seconds. If we increase the number of nodes and the fixed nodes to two, so the density is higher ($0.04u/m^2$), we can see that the coverage is nearly 100%, and the waiting time is very low (9 seconds).

Museum (British Museum): Values regarding density, affluence and entrance rates were obtained from the British Museum web page. For the contact rates we used the values obtained in [49] (SPM data set). More specifically, for a crowded environment (*first row of Museum scenario*), we consider the values obtained on February 21st, 2015 (Saturday). That day the total affluence reached 22,595 people, and the peak hour interval was from 14:00 to 15:00, with an input rate of 3673 persons/h. During this hour we consider that about

Scenario	Area km^2	N	Density u/m^2	F	RR u/h	λ c/h	Λ c/h	Cov. %	T_d s	T_w s
Mall	12.5	1,850	0.150	5	720	0.06	0.11	99.6	208.6	31.9
Mall	12.5	125	0.010	5	180	0.06	0.11	82.2	1275.1	539.9
Mall	12.5	125	0.010	10	180	0.06	0.11	83.5	842.0	495.9
Park	200	8000	0.040	2	360	0.05	0.18	99.9	39.1	8.6
Park	200	800	0.004	1	36	0.05	0.18	99.6	560.4	85.4
Museum	92	7,500	0.082	2	1836	0.02	0.10	99.7	185.4	24.0
Museum	92	1,000	0.011	2	400	0.02	0.10	98.0	864.8	181.8
Museum	92	1,000	0.011	10	400	0.02	0.10	98.1	550.8	174.6

TABLE I: Main performance parameters for the different case studies. NOTE: RR refers to the renewal rate, and it is expressed as users per hour (u/h); λ and Λ are expressed in contacts per hour between pairs (c/h); T_d is the diffusion time for 75% coverage, and T_w is the waiting time.

15,000 persons are inside the museum[8]. The results show that the coverage is nearly 100% and, the waiting time is about 25s. Finally, for a non-crowded environment (*second and third rows of Museum scenario*), we consider January 7th, 2015 (Wednesday) from 11:00 to 12:00, with an input rate of 800 users/hour and 2000 users in the museum. The results show a high coverage ratio, with a waiting time of 3 minutes, and increasing the number of fixed nodes, as in the Shopping mall scenario, has little impact on the coverage and waiting time.

From the previous scenarios we can see that, in crowded environments the coverage is nearly 100%, and the waiting time is very low (less than 30 seconds). Even in not crowded environments, the coverage remains very high, and the waiting time is very reasonable. Experiments show that increasing the number of fixed nodes does not have a significant impact on performance. The reason is that the number of fixed nodes is relatively low in comparison with the number of mobile nodes, and so the diffusion process is mainly performed between mobile nodes. Regarding the amount of data transmitted, for example, in the crowded mall, it supposes a global amount of nearly 2TB (1GB$\times$1850 nodes) of data transmitted in about 3 minutes with no cellular cost (as a reference, 1 to 5GB is the typical month limit plan of data carriers).

VI. Conclusions

In this paper we considered the combination of opportunistic communications and the new 5G wireless technologies like WiGig high-speed links to achieve faster content dissemination among nearby devices. We specifically focused on distributing large amounts of information among visitors of open areas (shopping malls, museums, parks, etc.) through users' mobile devices.

Based on *Population Processes*, we proposed a model to understand the fundamental trade-offs of the performance of information diffusion based on several parameters such as user density, contact rate, etc. We also showed that, when the user density is high, the diffusion is mainly performed through opportunistic contacts between mobile nodes and the coverage achieved was close to 100%. Regarding the arrival and departure of users, the impact was shown to be more important when user density is low.

We observed that, in the evaluated scenarios, the diffusion was fast enough to dynamically update the information among all participating members, avoiding the need for users to move close to fixed spots to receive the updated information. We consider that the presented model and closed-form expressions can be useful for the practical deployment of fixed information spots in open places, and to determine the practical coverage and diffusion time associated to content dissemination processes.

[8]Note that we are considering that half of the people are using the mobile application to obtain information, so user density and renewal rate are 7,500 users and 1836 u/h respectively.

Acknowledgments

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