Information Dissemination using Human Mobility in Realistic Environment- (E-Inspire)

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***Abstract*—Dissemination of information in mobile adhoc networks has lately picked up lot of interest. Some studies argue that the dissemination in these networks should be contained while some argue that it should not. Research has found that it depends on the type of the application that is considered. For example, dissemination of mobile viruses should definitely be contained however, dissemination of emergency information should not. Moreover, in the regions where there is less connectivity and very few mobile devices, dissemination of packets is highly impacted. Towards this, we would like to propose a mechanism that could enhances dissemination of information in a sparsely populated mobile adhoc environment. We use the concept of metapopulation model and epidemic model and the results obtained after the analysis of the dataset provided by D4D Organizers. From the results we obtained, we could say that in our model we could reach the epidemic state in dissemination process using the movement pattern of the users (derived from the dataset provided by D4D organizers).**

***Index Terms*—Human Mobility, Information Dissemination, Variable Density.**

I. Introduction

Due to vast developments in wireless devices and mobile network, recently Pocket Switched Network (PSN) has been introduced [1]–[3]. A PSN is a mobile adhoc network formed when devices carried by humans interact with each other. Due to the human aided mobility, PSNs closely follow human mobility characteristics. Human mobility has vastly been studied and many spatio-temporal characteristic properties have been identified that define human mobility. Some of these properties include jump length, pause time, radius of gyration, frequency of visits, etc. Recently, studies have revealed that human mobility not only has spatio-temporal dimension but also has social dimension [4], [5]. It was also revealed that different characteristics of human mobility closely follow truncated power law. It was however also shown that the truncated power law was also due to the sampling of the data [6]. Due to the vast identified properties of human mobility, models usually use only some features of human mobility instead of incorporating all. Some models use temporal characteristics in form of periodic, aperiodic and sporadic nature while some use spatial like centric, orbital, random or social like group movement, etc. In [7] authors survey different mobility models using above mentioned features and clearly bring out the differences between the models.

Recently, epidemics across population have been the focus of lot of research and various models has been proposed. An epidemic model typically contains two states: Susceptible(S) and Infected(I). However, there are other states also used like Recovered(R), exposed or Latent(E) and Passively immune(M) by some models. A typical epidemic model consists of combinations of these states. A comprehensive survey about the epidemic model could be found in [8], [9]. In Communication networks, information dissemination has been closely related to epidemics across the population and consider SIS or SIR epidemic model, for example, [10]. Further, in communication networks, information dissemination has been shown to be influenced by many factors like bursty data [11], strength of the tie [12], source of the infection, number of infected devices, human mobility parameters [13], location preference [14], network structure [15], activity pattern [16], device characteristics [13], [17], altruism [18] etc. However, mostly the focus has been limited to the study of effects of human mobility on information dissemination. Recently, [19] showed that human mobility in some time can speed up the information dissemination rate while can also in some cases suppress the information dissemination rate. The speed up relates to higher probability of meeting susceptible population while reduction related to isolation of the infected device.

Moreover, mostly the models based on epidemics using human mobility considered homogenous population well spread across the area. However, Watts et al in [20] used the hierarchical metapopulation model for the dissemination process. In their model, Watts et al argued that clusters are evident in a large population and they affects the epidemic spread. They assumed SIR type epidemic model and allowed human mobility in terms of changing clusters with a probability related to levels of clusters jumped. Fig 1 shows clustering of humans into groups and possible transitions that could happen. Moreover, in Watts et al model, uniform distribution of population in the clusters was considered. However, in realistic case, there is a non-uniform distribution of population in the clusters and the overall population constantly changes with respect to time. This affects the dissemination process in terms of time taken to spread the epidemic in the area.

In a PSN, however, where the structure of the network is dependent on the humans and the characteristics of mobile device, we are interested to investigate how information dissemination takes place in the dynamic population in contrast to [13] where constant population size was used. Towards this, we use insights from the spreading in metapopulation model [21], data provided by D4D organizers and epidemic model to formulate our model. In our model, the population is non-uniformly divided into communities. These communities

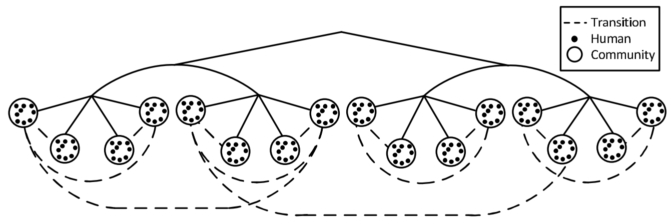


Fig. 1. Hierarchical Metapopulation Model [20].

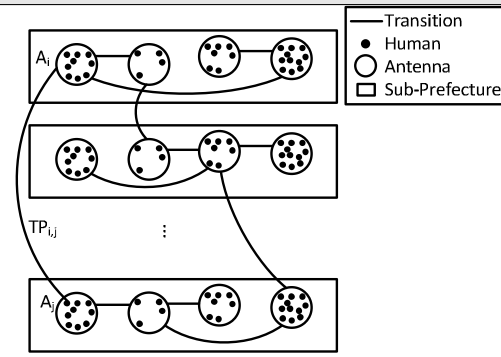


Fig. 2. Modified metapopulation Model for uneven population distribution and antenna-subprefecture hierarchy. Movement could occur between neighboring antenna. The neighboring antennas could be in different subprefecture. Here, a person from antenna A_i could move to antenna A_j with a probability $TP_{i,j}$. The antennas A_i and A_j belong to different subprefecture.

are the antennas to which the population is associated to in the country. A group of antennas formulate a bigger community known as sub-prefecture and further, collection of sub-prefectures form a country. According to the metapopulation model, a user transits from one community to anther using a transition probability, in our model this transition probability between two antennas is calculated through the analysis of the dataset provided by the D4D organizers and through the graph generated using voronoi tessellation. The transitions could happen between antennas of different subprefecture as two neighboring antennas could be in different subprefecture (Cf. fig. 2). More details on how we calculate transition probability can be found in section II-B. As a person can move within a community also, in our model, we assume that devices can also move within the community (antenna).

As we are concentrating on PSN, a device in a PSN can pair up with a device within its range and can transmit its data packets to the paired devices. A device having data packet to transmit is said to be in Infected(I) state while those not having the packet are considered to be in Susceptible(S) state. Once the device in S state has the information it changes its state to I. We use recovery rate also so as to model realistic scenario. The recovery rate would mean that the devices are only willing to transmit the information for certain period. As mentioned before, characteristics of a PSN is dependent on the humans. Human can switch off the device and can reopen them any time causing changes in the structure of the PSN due to change in the number of active devices. To capture this effect we use the Latent state (E) of the epidemic model. To distinguish between devices that are latent but Susceptible and are latent but Infected, we divide E into two states E_S and E_I. A device in E_S or E_I state does not participate in dissemination process. However, only devices in S and I participate in the dissemination process. Further, more comprehensive details about the model are mentioned in section sec. III.

Further, in this paper, we first analyze the dataset provided in section sec. II. We then provide detailed description of the model in section sec. III. We then provide results obtained in section sec. IV and finally conclude in section sec VI after providing future work in sec. V.

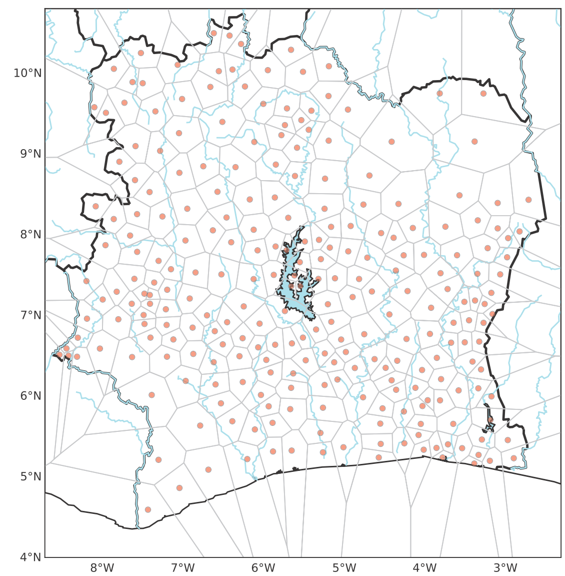
II. Data Analysis

In this section, we further analyze data collected by Orange for the region of Ivory Coast than what has been provided in [22]. The data is based on the calls made in the region of Ivory Coast and the mobility of the users. The region of Ivory Coast has been assigned number of antennas and is divided into sub-prefectures. The dataset contains the locations of these antennas and sub-prefectures in longitude and latitude format. The dataset is further divided into four sub-datasets out of which we are interested only in sub-dataset **SET2TSV** and sub-dataset **SET3TSV**. Sub-dataset **SET2TSV** and **SET3TSV** contains pruned mobility patterns of the users over 5 months. These sub-datasets has been formed by the logging of call information of the users in Ivory Coast. The sub-dataset **SET2TSV** relates users with antennas while sub-dataset **SET3TSV** relates users to sub-prefecture. Both these sub-datasets have information like, user, time, antenna or sub-prefecture. Moreover, another difference between the two sub-datasets is that sub-dataset **SET2TSV** has been sampled for 50,000 users while sub-dataset **SET3TSV** has been sampled for 500,000 users over 5 months. However, mobility from these two sub-datasets can only be inferred as the id of antennas and the sub-prefectures has been logged when the call was made and not the actual location of the user. Moreover, we are interested in the analysis datasets with antennas and sub-prefectures location and sub-dataset **SET2TSV** to get useful information that could be used in our proposed model.

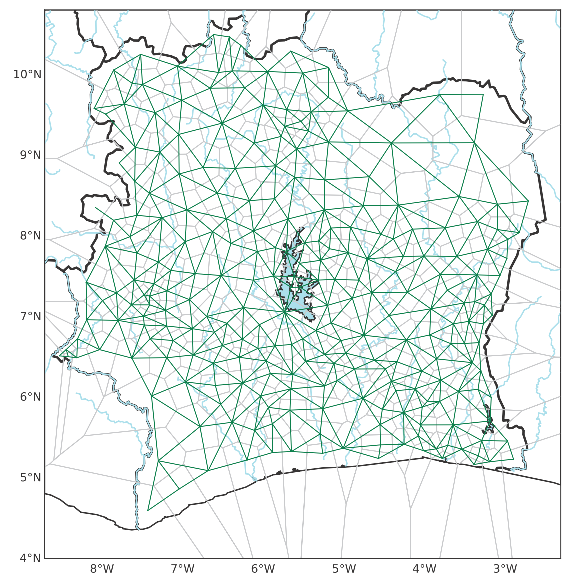
A. Analysis Dataset SUBPREF_POS_LONLAT.TSV and ANT_POS.TSV

We first analyze dataset **SUBPREF_POS_LONLAT.TSV**. We use the position information of the sub-prefectures to provide the visualization of the sub-prefectures in the region of Ivory Coast and visualize the Voronoi tessellation (Cf. fig. 3(a)). Using Voronoi tessellation we then generate a graphical structure that connects all sub-prefectures with common Voronoi edges. As an edge in the graph could lie well outside the country boundaries, we remove all those edges that bypass the country. We call the remaining graphical structure $G_{sub-pref}$, (Cf. fig. 3(b)).

Similar to sub-prefectures dataset, dataset **ANT_POS.TSV** has been provided for antenna locations. We perform similar procedure on this dataset and generate Voronoi tessellation, (Cf. fig. 4(a)), and the graphical structure $G_{antenna}$, (Cf. fig. 4(b)). Further, we assume that each antenna is assigned to a sub-prefecture. Depending on the Voronoi tessellation of the sub-prefectures we then provide an estimate of which antenna is assigned to which sub-prefecture (Cf. fig. 5(a)). This leads us to further visualize fig. 5(b) which is the frequency of number of antennas in the sub-prefectures. As

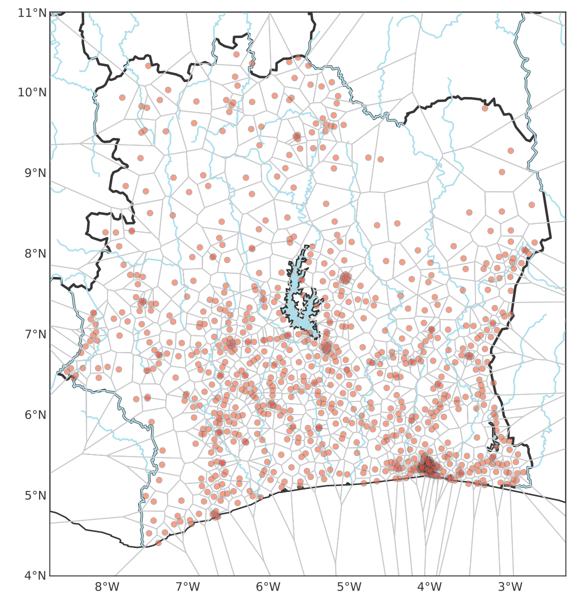


(a) Voronoi tessellation for the Sub Prefectures in Ivory Coast with Sub Prefecture locations.

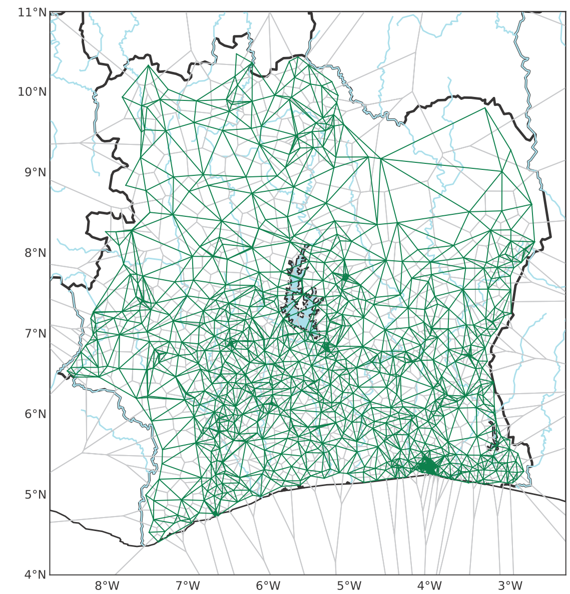


(b) $G_{sub-pref}$.

Fig. 3. Analysis of dataset **SUBPREF_POS_LONLAT.TSV**.



(a) Voronoi tessellation for the antennas in Ivory Coast with antenna locations.



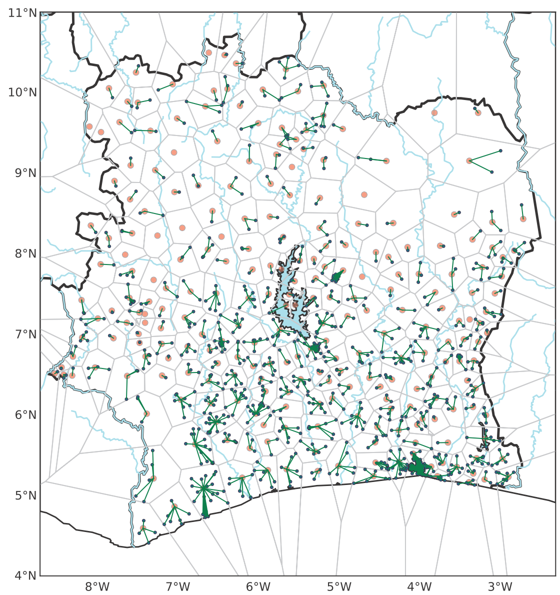
(b) $G_{antenna}$.

Fig. 4. Analysis of dataset **ANT_POS.TSV**.

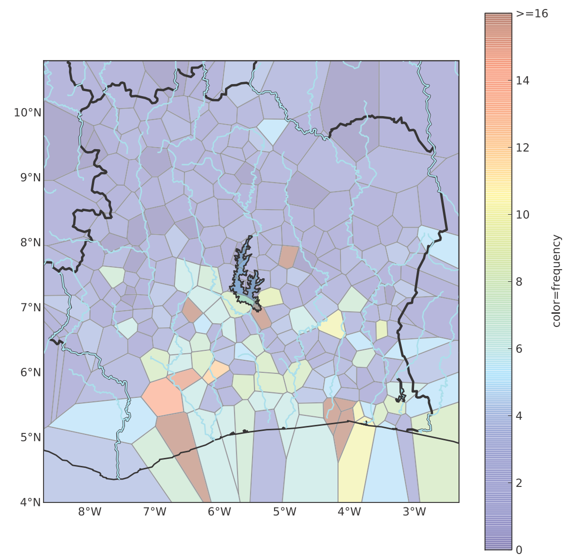
we have estimated the region of sub-prefecture using Voronoi tessellation, the results of the frequency of number of antennas in the sub-prefectures slightly vary from the frequency of antennas when actual sub-prefecture region in Ivory Coast are used, (Cf. fig. 6).

B. Analysis Sub-Dataset SET2TSV

As the sampling of the information in the datasets is based on the calls made, the data has very high percentage of users calling from same location. This sampling hampers the correct estimation of human mobility. We could only infer the mobility pattern of the user. Lack of actual user coordinates leads us to map the mobility of the user on $G_{antenna}$ to get an estimate of the user mobility. This would give us what antennas a user would have connected to while they were moving. This would give us valuable information like how many times a user stayed at a location and how many times the user took a certain path. Further, to estimate the mobility of the user we use shortest path between two antennas in the graph $G_{antenna}$. Thus, from the sub-dataset **SET2TSV** we map the mobility of one user using the $G_{antenna}$ and determine the antennas that the user might have been contacted to by the user while moving, (for user id 48930 Cf. fig. 7(a)). In the figure 7(a) the blue edges mark the edges that user traversed. The thickness of the edges determines the number of times the user traversed through that edge. On the other hand, the size of the node in the graph is determines the number of times the user has stayed at that antenna. We then perform this process for all the users in the sub-dataset **SET2TSV** for all the period and determine



(a) Antenna connected to the Sub Prefectures in Ivory Coast.



(b) Frequency of antennas in the Sub-Prefectures in Ivory Coast estimated using Voronoi tessellation.

Fig. 5. Antennas in the Sub-Prefectures.

a transition probability matrix ($Tm_{antenna}$). The $Tm_{antenna}$ contains the normalized weight of the edges accumulated over 5 month period, (Cf. fig. 7(b)).

We now describe our information dissemination model using the transition matrix formed in the section sec. II-B and metapopulation model in the next section.

III. Model

Consider N devices to be non-uniformly distributed in the region. The non-uniformity leads to a community structure in the region. We assume that the devices in a community (c) are associated to one and only one antenna in the region at any given time. As discussed in the introduction section, collection of these antennas form sub-prefecture and collection of sub-prefectures form a region. Further consider, the number

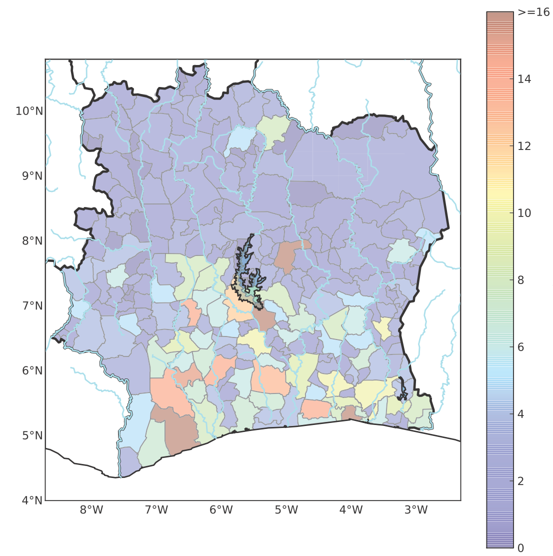
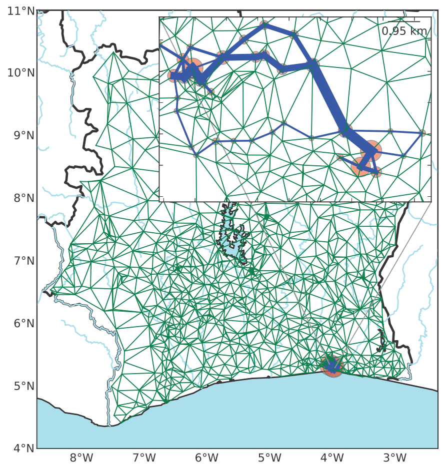


Fig. 6. Actual antenna frequency in Sub-Prefectures in Ivory Coast.

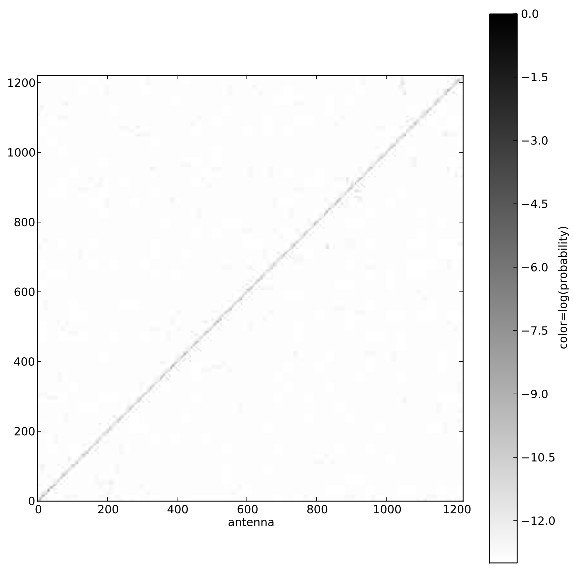
of antennas(communities) as N_c. As argued by Watts et al, community structure is evident in the population in a realistic scenario. A transition from one community to anther occurs with a probability [20] and the nature of the community [14]. This probability plays an important role in determining which community has to be joined. We use transition probability matrix ($Tm_{antenna}$) calculated after doing the data analysis in section sec. II-B to determine the jumps from one community to another. The transition probabilities also provide us the probability of staying in the same community. Staying in the same community would mean that the device has not moved out of the community. This would not restrict the movement of the device within the community bounds, i.e., the device would be free to move within the community bounds.

In-order to study the dissemination process, we assume the devices to be in any of the four states, S, I, E_S or E_I. State S would mean that a device is not having the information and is susceptible to receive it on the other hand state I would mean that the device has the information and will readily transmit it to other devices in its transmission range. Irrespective of whether a device is in state S or state I, the capability of the device to transmit or receive depends on the user. It could be possible that a device has the information but has been switched off by its user. This would hamper the transmission of the information from the device to other devices. Following the same argument, if a device does not have the information and it is switched off it would not be able to receive the information from other devices. We call such state of devices as latent state of a device and term them to be in state E_I and E_S respectively. At a later time, a device in a latent state could be switched on, this would mark the transition in the state of the device from either E_I and E_S to I and S respectively.

It has been argued in research that communities affect the dissemination of the information. The rate of the dissemination process within a community is more than the rate at which dissemination process takes place outside the community. This makes us to constrain the devices in state I to be able to



(a) Antennas reached by user 48930 while moving for first 2 weeks.



(b) Transition Probability Matrix.

Fig. 7. Sub-Dataset **SET2TSV**.

only transmit information to devices in the same community (having same antenna id), in state S and within its Tx. Further, in epidemic, each community has a different infection rate, β_c where c is a community. This is because of many factors like, density of the population and immunity strength of population in the community. Moreover, in a population an infected person has a recovery rate, δ_x where x is the person. In PSN infection rate and recovery rate would mean that devices in community c and in state I are willing to transmit the information with the rate β_c while a device x in state I is rejecting the information after some time with a rate δ_x. However, we assume that δ_x for all device in a community

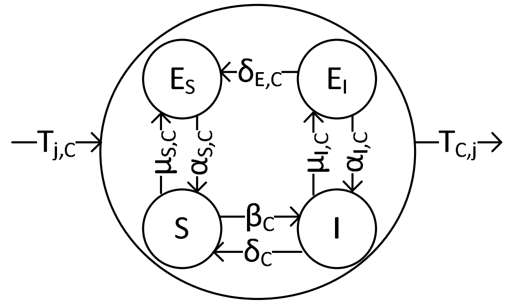


Fig. 8. State diagram with states S and I and their latent states E_S and E_I respectively with transition rates between states.

is same and is δ_c. In order to model β_c we use the area of the community as eq. 1. Thus, the type of epidemic model we consider is SIS with two additional states E_S and E_I.

$$\beta_c = 1 - \frac{A_c}{A_{max}} \tag{1}$$

where A_c is the area or the community c within a region and A_{max} is the area of the region under consideration.

The state diagram for a device to make a transition from one of the states to another can be given by fig. 8. Here, the transition from state S to state I at time $t + \Delta t$ depends on the infection rate β_c. In a community, devices can join as well as leave. The incoming rates and the outgoing rates are given by transition matrix found in sec. II-B. We call them as $T_{j,C}$ and $T_{C,j}$ where j is another community. The transition rates between S and E_S are given by $\mu_{S,C}$ and $\alpha_{S,C}$ while that between I and E_I are given by $\mu_{I,C}$ and $\alpha_{I,C}$.

In a community i, let S_i be the number of devices in state S at time t, I_i be number of devices in state I at time t, $E_{I,i}$ be number of devices in state $E_{I,i}$ at time t and $E_{S,i}$ be number of devices in state $E_{S,i}$ at time t. Considering initial conditions as $S(0) = N - \varepsilon$, $I = \varepsilon$ where $\varepsilon > 0$, from the model described above, we could formulate rate equations for one community i using mean field as follows:

$$\begin{aligned} \frac{\mathrm{d}S_i}{\mathrm{d}t} &= -\beta_i \frac{S_i I_i < k_{R,i} >}{N_i} \\ &\quad + \sum_{\forall j \in C; j \neq i} T_{j,i} S_j - \sum_{\forall j \in C; j \neq i} T_{i,j} S_i \\ &\quad + \delta_i I_i - \mu_{S,i} S_i + \alpha_{S,i} E_{S,i} \end{aligned} \tag{2}$$

$$\begin{aligned} \frac{\mathrm{d}I_i}{\mathrm{d}t} &= \frac{\beta_i S_i I_i < k_{R,i} >}{N_i} \\ &\quad + \sum_{\forall j \in C; j \neq i} T_{j,i} I_j - \sum_{\forall j \in C; j \neq i} T_{i,j} I_i \\ &\quad - \delta_i I_i - \mu_{I,i} I_i + \alpha_{I,i} E_{I,i} \end{aligned} \tag{3}$$

$$\begin{aligned} \frac{\mathrm{d}E_{S,i}}{\mathrm{d}t} &= \mu_{S,i} S_i - \alpha_{S,i} E_{S,i} + \delta_{E,i} E_{I,i} \\ &\quad + \sum_{\forall j \in C; j \neq i} T_{j,i} E_{S,j} - \sum_{\forall j \in C; j \neq i} T_{i,j} E_{S,i} \end{aligned} \tag{4}$$

$$\begin{aligned} \frac{\mathrm{d}E_{I,i}}{\mathrm{d}t} &= \mu_{I,i} I_i - \alpha_{I,i} E_{I,i} - \delta_{E,i} E_{I,i} \\ &\quad + \sum_{\forall j \in C; j \neq i} T_{j,i} E_{I,j} - \sum_{\forall j \in C; j \neq i} T_{i,j} E_{I,i} \end{aligned} \tag{5}$$

$$\begin{aligned}\frac{\mathrm{d}N_i}{\mathrm{d}t} &= \sum_{\forall j\in C; j\neq i} T_{j,i}S_j - \sum_{\forall j\in C; j\neq i} T_{i,j}S_i \\ &+ \sum_{\forall j\in C; j\neq i} T_{j,i}I_j - \sum_{\forall j\in C; j\neq i} T_{i,j}I_i \\ &+ \sum_{\forall j\in C; j\neq i} T_{j,i}E_{S,j} - \sum_{\forall j\in C; j\neq i} T_{i,j}E_{S,i} \\ &+ \sum_{\forall j\in C; j\neq i} T_{j,i}E_{I,j} - \sum_{\forall j\in C; j\neq i} T_{i,j}E_{I,i} \qquad (6)\end{aligned}$$

where $N = \sum_{\forall i\in C} S + \sum_{\forall i\in C} I + \sum_{\forall i\in C} E_S + \sum_{\forall i\in C} E_I$, $< k_{R,i} >$ is the average degree of the devices in the network between devices in the community i with R being the area of the community i. For a network, $< k_{R,i} >$ could be modeled as eq. 7 [23]. Using the probability of connection in an area with a population and the attenuation factor (Communication network parameters), average degree could be defined as integral of probability of connection for a given density over the area, yielding eq. 7

$$\begin{aligned}< k_{R,i} > &= a2\pi\overline{\rho}\frac{r_0\tau}{1-\tau} * \qquad (7)\\ &\left[R\left(1+\frac{R}{r_0\tau}\right)^{1-\tau} - \frac{r_0}{2-\tau}\left(1+\frac{R}{r_0\tau}\right)^{2-\tau}\right]_{2l}\end{aligned}$$

where $\overline{\rho}$ is the density of devices in the area, $r_0 = \sqrt{(A/(N\pi))}$ and a and τ are the communication network parameters > 0. The eq. 7 is modeled for static population, however, when mobility is introduced $< k_{R,i} >$ would change over time. This could be modeled as eq. 8 using p as the pause time of a device on a location [24].

$$< k_{R,i} > \approx \frac{Nr_0}{3}\left((4-2p+p^2) - \frac{4}{\pi}p^2 r_0 - 3(1-p)r_0^2\right) \qquad (8)$$

Further, analyzing the eq. 3, we could say that there would be a growth in the population of devices in I when $\frac{\beta_i S_i < k_{R,i} >}{N_i} + \sum_{j=1}^{C} T_{j,i} - \sum_{j=1}^{C} T_{i,j} - \delta_i - \mu_{I,i} > 0$. This gives basic reproduction number as $\frac{\frac{\beta_i < k_{R,i} >}{N_i} + \sum_{j=1}^{C} T_{j,i} - \sum_{j=1}^{C} T_{i,j}}{\delta_i + \mu_{I,i}} > 1$ where epidemic would takeoff.

IV. Simulation and Results

We perform simulation in Python. Initially, each device operates in omnidirectional mode with the transmission range $Tx = 1km$. We consider $N = 5000$ in an area of $Area \approx 710 * 756 km^2$ (Ivory Coast region). All the results use $Tm_{antenna}$ for mobility. We assume initially $N-1$ devices are in susceptible state and only one device is in infected state. Out of these $N-1$ susceptible devices some devices are in latent state.

As the preliminary results, we provide results for the information dissemination in the population using our model, (Cf. fig. 9). This result was obtained for the case when there is single infected device, $\delta_i = 0.975 \forall i \in C$, β_i as defined in eq. 1. The result shows the percentage of infected nodes over time

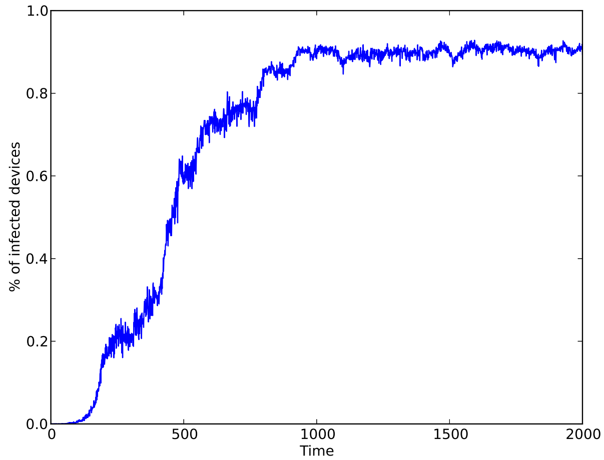


Fig. 9. The time taken to reach the epidemic state in the dissemination process.

normalized over active population in the area. Initially, due to more number of susceptible devices the rate of change in devices in I is more however, over time it reaches an epidemic state.

V. Future Work

Here we presented preliminary results. However, more comprehensive results are to be obtained and to be verified to see the effect of various parameters used in the model. Moreover, currently we have not used birth and death process, i.e., addition of new devices and removal of old devices. We also would like to incorporate heterogenous population density in our model. Addition of such concept could add more realism to the model. We would like to incorporate it as the future work. Further, a device in PSN can be equipped with multiple small antennas which could help in enhancing transmission radius for the device. Using multiple antennas gives rise to a beam of certain length and width. This technique is known as beamforming. Effects of beamforming have already been studied on information dissemination for both static and mobile networks with positive results [13], [25]–[28]. Incorporating beamforming in the model would definitively give an edge and help in enhancing information dissemination. A brief overview of how it could be done is explained in sec. V-A below.

A. Adding Beamforming to the model

Dissemination process could be enhanced using different ways. Some ways studied in literature are mobility and beamforming. Beamforming is a technique of using multiple device antennas in-order to get a long directional beam (long range link) with the same operational power as that of omnidirectional beam. Thus, in our model, we would also like to use beamforming. We assume that each device is equipped with m device antennas (DAs), where m could be different for different devices. Initially all devices use one DA for omnidirectional transmission with the omnidirectional transmission range being Tx. The Tx could also be different for different devices. Beamforming is done by devices in state I. In the landmark paper by Watts and Strogatz, [29], the authors showed that using very few long range links network diameter can be considerably reduced while network clustering is maintained thereby escalating the dissemination phenomenon. We use this result to state that only 0.01% of the devices in state I are randomly chosen to beamform. The selected devices randomly choose m_x DAs from m available DAs to determine length and width of the beam. The best direction of the beam is chosen based on which direction has the maximum number of devices in S state. The beamforming device then beamforms in that direction, infects the susceptible devices and returns back to omnidirectional case. Further, beamforming is achieved by special arrangement of DAs. Some realistic ways include Uniform Linear Array Antenna model (ULA) [30]. Using m_x DAs according to ULA model would lead to a beam of length $m_x * Tx$ with different beamwidth for different angles $\in [0, 2\pi]$. We would use these unique directions and gain(beam) patterns of ULA model and determine number of devices in state S the beamforming device could connect using that direction. The direction having the maximum number of devices in S state is chosen for beamforming. let the chosen direction be θ_b. The width of the beam in the direction θ_b for the ULA model is given using eq. 9

$$g(\theta, \phi) = \frac{u(\theta, \phi)}{\frac{1}{4\pi} \int_0^{2\pi} \int_0^{\pi} u(\theta, \phi) \sin\theta d\theta d\phi} \tag{9}$$

where θ is angle with the z-axis, ϕ with the xy-plane, $u(\theta, \phi) \propto \left(\frac{\sin(m\psi)}{m*\sin(\psi)}\right)^2$, $\psi = \pi\Delta(\cos\theta - \cos\theta_b)/\lambda$ and Δ is the distance between 2 DA's.

Adding beamforming to the model would change the $< k_{R,i} >$ as 0.01% devices would beamform. We would like to use this concept and build our model towards enhancing information dissemination in realistic environment.

VI. Conclusion

In this paper we presented a model where information dissemination across the population is studied using movement probability from one community to another calculated using the dataset provided by the D4D organizers. We used concepts like epidemic model and metapopulation in our model. To realize the information dissemination process we have used SIS epidemic model with two additional states E_S and E_I. E_S and E_I states are the latent states where devices in these states are not involved in dissemination process. Our result shows that epidemic state could be reached in the our current setting.

VII. acknowledgement

The authors thank D4D organizers for providing the data.

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