Understanding the Spread of Epidemics in Highly Partitioned Mobile Networks

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Abstract—In this paper we introduce a model for analyzing the spread of epidemics in a disconnected mobile network. The work is based on an extension, to a dynamic setting, of the eigenvector centrality principle introduced by two of the authors for the case of static networks. The extension builds on a new definition of connectivity matrix for a highly partitioned mobile system, where the connectivity between a pair of nodes is defined as the number of contacts taking place over a finite time window. The connectivity matrix is then used to evaluate the eigenvector centrality of the various nodes. Numerical results from real-world traces are presented and discussed.

Index Terms—epidemics spreading, wireless mobile networks, eigenvector centrality, clustering, topography

I. INTRODUCTION

In this paper, we aim at characterizing the spreading power of nodes in a mobile disconnected network, where the possibility of “spreading” an epidemic is limited to sporadic contacts between pairs of nodes. The problem is of interest for a number of reasons, the prominent one being the research efforts towards the definition of an architecture for Delay Tolerant Networks (DTNs) [1], [2]. DTNs are networks in which the existence of a path between any pair of nodes is not taken for granted. Differently from conventional IP networking paradigm, DTNs are able to operate in the presence of frequent network partitions. In DTNs there is – roughly speaking – no notion of network any longer: information can diffuse in the system by means of (i) nodes mobility: a device conveys information while moving around (ii) opportunistic forwarding: messages are passed from a node to another one when they get in contact. Further, most DTN application scenarios envisioned so far are characterized by a high degree of dynamism, due to the fact that nodes may be, e.g., PDAs carried around by people [3] or buses which are used to spread information on a metropolitan area [4]. If in DTN there is no notion of network, clearly also the notion of “route” blurs: it is therefore imperative to use, in such settings, some form of “epidemics spreading” for accomplishing system-wide communications [5], [6], [7].

The starting point for our analysis is the work carried out by two of the authors on the spreading power of nodes in a static setting [8], [9]. The work therein focuses on the notion of eigenvector centrality (EVC), shown to be a meaningful measure of the ability of the nodes to spread an epidemic in the network. The EVC is computed as the eigenvector relative to the spectral radius (i.e., the largest eigenvalue) of the adjacency matrix of the network. Such a procedure is shown to produce a smooth measure, which can be used for studying the spread of epidemics [9]. Further, it implies a natural way of defining clusters in the network. The resulting network topography can be used to define regions, each region being characterized by the fact that epidemics spread extremely fast therein.

The main contribution of this paper is the extension of the eigenvector centrality principle to more dynamic scenarios. We will indeed focus on how to extend the topographic picture, with its obvious advantages for studying epidemic spreading, to a dynamic network — one in which the links are time-dependent. Our aim is to take a mobility pattern as input, to determine the time-dependent links, and finally to produce a topographic analysis analogous to the static case — with a smooth centrality function over the nodes, regions defined so as to correspond to well connected subgraphs, and a meaningful connection to the nodes’ roles in spreading. Thus we want to define some kind of time-averaged or time-integrated connectivity matrix, with non-negative link weights. Given a suitable definition of connectivity matrix, we can apply the EVC analysis to study its topographic properties. We introduce the notion of $T$-tolerant connectivity matrix, whose $(i,j)$-th entry equals the number of contacts between nodes $i$ and $j$ over a time window of length $T$.

The remainder of this paper is organized as follows. In Sec. II we review the basic EVC concept and its application to static settings. In Sec. III we introduce the notion of $T$-tolerant connectivity matrix and show how to build it. In Sec. IV we show some numerical results, obtained from real-world mobility traces, and discuss the properties of the correspondent systems. Sec. V concludes the paper pointing out some directions for future work.

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1The term “connectivity matrix” can be somehow misleading, in that we are mostly interested in disconnected scenarios, where a randomly taken snapshot of the network returns a disconnected graph.
II. EIGENVECTOR CENTRALITY, TOPOGRAPHY, AND SPREADING

In this section we present a brief review of earlier work involving a “topographic” view of the structure of networks with undirected links. This work is presented in detail in [8] — which presents the basic structural analysis, based on eigenvector centrality or EVC [10] — and in [9] — which shows the utility of this analysis for understanding and predicting the progress of epidemic spreading over the network.

A. Previous work

A fundamental problem in network analysis is the problem of clustering. That is: given a network topology (possibly with weights on the links), and assuming that the network is symmetric and connected, how do we then define and identify subgraphs of the whole network which, in some well defined sense, consist of nodes which “belong together”?

One meaningful and useful notion of “belonging together” is that of “being well connected”. This point of view states that the clusters (subgraphs) of a network are better connected internally than they are to other clusters. Two of us [8] have constructed a precise version of this kind of clustering criterion. That is, one can define “well-connectedness” in a number of ways; but one definition — valid for a single node — is that the node be well connected to nodes that are well connected. This is of course a circular definition, which however is readily formulated mathematically [8], [10].

The resulting single-node measure of well-connectedness is termed “eigenvector centrality” or EVC [10]. Let us consider a graph model of the network topology and denote by $A$ the corresponding adjacency matrix. The EVC of a node $i$ is defined as being proportional to the sum of the EVC of $i$’s neighbors:

$$e_i = \frac{\sum_{j=nn(i)} e_j}{\lambda},$$

(1)

where $nn(i)$ denotes the set of neighbors of node $i$. We can rewrite (1) in a compact matrix form:

$$A \cdot e = \lambda e,$$

(2)

where $e$ represents the vector of nodes’ centrality scores. Otherwise stated, $e$ is the eigenvector of $A$ relative to the eigenvalue $\lambda$. A number of reasons [8], [9] suggests to choose $\lambda$ as the maximal eigenvalue $\lambda_{\text{max}}$. Due to the fact that $A$ is nonnegative, $\lambda_{\text{max}} \geq 0$ and all the components of $e$ are nonnegative [11].

EVC can be exploited to define clusters as follows. We note that, because of the dependence of a node’s EVC on that of its neighbors, the EVC may be regarded as a “smooth” height function over the network. This smoothness motivates the appeal to topographic notions. That is: local maxima of the EVC are regarded as being the most well-connected node in a region of good connectivity. In topographic terms, these local maxima are mountain peaks. Each “mountain” (region of good connectivity) is then defined by its peak, plus a rule for membership of other (non-peak) nodes [8] in the well-connected cluster. A simple membership rule is that each node belongs to the same mountain as does its highest (EVC) neighbor. In other words: a node is connected to the cluster of its best connected neighbor. With this rule, essentially all nodes are assigned uniquely to one mountain; the mountains are then the well connected clusters of the graph. These are termed regions in the earlier work, and we will adhere to that usage here.

In more recent work [9] it has been shown that this smooth definition of well connectedness, and the resulting notion of regions, are very useful for describing and understanding the time and space (network) progression of an epidemic on an undirected network. The basic idea is that an infection front tends to move towards neighborhoods of high connectivity (EVC), because the spreading is fastest in such neighborhoods. This says in other words that the front naturally moves “uphill” over EVC contours—which in turn implies that, in general, spreading will be faster within regions (mountains) than between them. These ideas, and related ones, have been described in detail, and confirmed in simulations, in [9].

Some important points from this work which are relevant for the present paper are:

- The importance of a node to the process of epidemic spreading may be roughly measured by the node’s eigenvector centrality.
- Regions, as defined by the steepest-ascent rule, are clusters of the network in which spreading is expected to be relatively rapid and predictable. (Here “relatively” simply means compared to inter-region spreading.)
- Nodes whose links (“bridging links”) connect different regions play an important role in the (less rapid, and less predictable) spreading from one region to another.

One can readily identify two important directions for extending such work, which builds on the work described in the previous subsection. First, the described topographic approach is, in its present form, only applicable to a static network. Secondly, the analysis is thus far only applicable when some entity (researcher, manager, engineer, machine) has access to knowledge of the full topology of the network. The latter constraint stems from the fact that the EVC of any node is in fact dependent on the entire topology of the network—because it is taken from the dominant eigenvector of the network’s adjacency matrix, and because the network is (assumed) connected. Thus, an interesting question is how one can define local, distributed methods for finding the EVC distribution and the region structure of a given network. This question will not however be pursued in this paper, whereas we will rather concentrate on the first issue, i.e., how to extend the EVC analysis to a mobile disconnected system.

III. BUILDING CONNECTIVITY MATRICES FOR DISCONNECTED MOBILE NETWORKS

As outlined in the previous section, in order to carry out the EVC analysis we need to define a matrix detailing the possible interactions among nodes. In the case of wired networks, this
is an easy task, since it suffices to look at the existing links connecting the network nodes. In this case, we can build a binary matrix, which is actually the adjacency matrix of the graph representation of the network. When moving into the wireless domains, things change, in that we do not have physical connections any longer. Let us consider first the case of a wireless network in which all nodes are static. In this case, we can build a matrix $A$, that we call the connectivity matrix, by looking at the fact that two nodes are within mutual communication distance. In other words, the $(i, j)$-th entry is different from zero, $A(i, j) \neq 0$ if and only if nodes $i$ and $j$ are within mutual communication range, i.e., they can successfully transmit data. In both the cases considered (wired and wireless) the matrix $A$ we build depends on the network topology.

Things drastically change when we considered a mobile network. In this case, indeed, there is no standard notion of network topology we can rely on for building the connectivity matrix.

This task gets even more challenging if we focus on networks operated in the subconnectivity regime [12], in which, i.e., no giant component exists. We are actually interested in something stronger, i.e., looking at networks in which, at any given time instant, each node is isolated with probability close to one. The reason for looking at such scenarios comes from two distinct reason. The first is technology-driven, in that there are a lot of application scenarios in which such assumptions hold. Most of them fall within the category of Delay Tolerant Networks (DTNs) [2]. DTNs are networks that are able to work in the absence of instantaneous connectivity.

The connectivity in DTNs follows a random pattern, and is not taken for granted as in standard IP-based networks. DTNs include also Vehicular Ad hoc NETworks (VANETs), where the nodes are represented by cars, which may exchange data to run distributed services, including traffic monitoring, alert messages, personalized advertising etc.[13]. On the other hand, networks operating in this regime are also of interest, in that results in the field of network information theory state that connected networks present poor scalability properties [14], while mobility can be exploited, for a network operating in the subconnectivity regime, to achieve a scalable network model [15].

In a disconnected scenarios, where nodes are isolated most of the time, the only opportunities for transferring information is given by meetings. Nodes $i$ and $j$ are said to meet at time $t$ if at time $t^-$ they were not able to communicate data, while they could do so at time $t^+$. Meetings form a random pattern, which depends on (i) the mobility of nodes (ii) the random channel fluctuations. Meetings are characterized by (i) the IDs of nodes which get within mutual communication range (ii) the time at which the meeting takes place (iii) the duration of the meeting.

The basic idea for building the connectivity matrix $A$ is to consider an integrated version of the instantaneous network connectivity. Given a constant $T$, we construct the $T$-tolerant connectivity matrix $A_T$ by considering all the meetings taking place over a time window of length $T$. The $(i, j)$-th entry $A_T(i, j)$ equals the number of meetings taking place in the time interval $[t_0, t_0 + T)$, where $t_0$ is a given time instant.

The underlying idea is the following. If the link weight for a link increases with the strength or frequency of the connection — or, in other words, with the probability of spreading an “infection” over the link — then the analysis of this connectivity matrix may be expected to give useful information about how an infection (or message) is likely to be spread in a network of mobile nodes. In short: given a connectivity matrix with non-negative link weights, which may be interpreted to grow with increasing probability of spreading over the link, one can compute an EVC for all the nodes. Subsequent analysis is then the same as done in [8] and [9]; and because of this assumption about the link weights, the results should be useful for describing the likely process of spreading on the mobile network, and for giving insight into the roles played by various nodes in the spreading process.

The definition of the $T$-tolerant connectivity matrix is worth some comments. In particular, the choice of an adequate time window $T$ appears non-trivial. The value of $T$ shall be consistent with the nodes dynamics, so that the matrix $A_T$ gives rise to non-trivial results. If $T$ is too small, most entries of $A_T$ turn out to be zero, the network shows little connectivity and, hence the EVC analysis does not carry significant information. The parameter $T$ shall be understood as a kind of time constant of the system. In particular, we are interested in working around the value of $T$ for which the graph associated to the matrix $A_T$ gets connected. Such value depends on the mobility and is therefore out of the control of system designers. On the other hand, such value determines the time horizon over which the system is able to deliver messages, placing therefore a constraint on the class of applications which can be supported by the system.

This time-integrated version of the connectivity presents, however, also a shortcoming. Consider the example reported in Fig. 1, where we considered the graph $G_T$ (called the $T$-tolerant connectivity graph) which we can naturally associate with the construction of the matrix $A_T$. The graph $G_T$ has vertex set corresponding to the nodes in the network. There is a link between $i$ and $j$ if and only if there is a non-zero value in the corresponding entry of the matrix $A_T$. The link is labeled (or weighted) with the value of the entry. In the situation considered in Fig. 1 there are three nodes, $A$, $B$ and $C$. At time $t_1$, nodes $A$ and $B$ get within mutual communication range.

\[2\text{In particular, for a connected network of } n \text{ nodes, half of which act as sources and the other half as receivers, the per-connection throughput scales as } \Theta \left( \frac{1}{\sqrt{n}} \right), \text{ whereas in a mobile network with the two-hop relaying scheme in [15], the same quantity scales as } \Theta(1).\]
Thus, we set the corresponding entry in the connectivity matrix to 1, and add an edge \((A, B)\) of unitary weight in the graph \(G\). At time \(t_2\), node \(A\) meets with node \(C\). Also in this case we add an edge of unitary weight. At time \(t_3\), node \(A\) gets again in contact with node \(C\). The weight of the corresponding link is thus increased to 2. In the resulting graph, there is a path connecting node \(B\) to node \(C\). However, there is a timing (or ordering) issue that is not accounted for in this construction. Indeed, node \(B\) can successfully transmit information to node \(C\) (by using \(A\) as relay), but not vice versa.

![Graphical representation of the timing issue](image)

Fig. 1. Graphical representation of the timing issue. In the resulting connectivity graph, there exists a path between \(B\) and \(C\). Due to the dynamics, data originated from \(B\) can be delivered to \(C\), but not vice versa.

### IV. Experimental Results: Real-World Mobility Traces

In this section, we aim at verifying the properties, in terms of EVC distribution and spreading power of nodes, of various real-world deployments of disconnected mobile networks. In particular, we considered three classes of traces, generated in different experiments and available through the CRAWDAD database at Dartmouth College [16].

The first set of experiments were performed by Intel Cambridge and reported in [3]. In this case, the devices were iMotes, equipped with a Bluetooth radio interface, and carried around by people in (i) a lab at Cambridge Univ. (ii) people in the Intel lab at Cambridge (iii) attendees of IEEE INFOCOM05. Each iMote periodically scans the frequency range to check if other devices are present; each contact event is registered together with its timestamp and duration.

The second set of experiments refers to the DieselNet project at Univ. Massachusetts at Amherst [17]. In this case, a number of buses has been equipped with IEEE 802.11b-compliant access points, used for bus-to-bus communications. Each device records the time and location of the contacts with other buses in the system. In our analysis, the trace 30122005 has been considered.

<table>
<thead>
<tr>
<th>Trace</th>
<th>Number of Nodes</th>
<th>Measurement Time (s)</th>
<th>Number of Records</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intel Exp1</td>
<td>128</td>
<td>359075</td>
<td>2758</td>
</tr>
<tr>
<td>Intel Exp2</td>
<td>223</td>
<td>322387</td>
<td>6469</td>
</tr>
<tr>
<td>Intel Exp3</td>
<td>264</td>
<td>255168</td>
<td>27223</td>
</tr>
<tr>
<td>UMass</td>
<td>20</td>
<td>60475</td>
<td>456</td>
</tr>
<tr>
<td>Reality Mining</td>
<td>83</td>
<td>16417</td>
<td>34683</td>
</tr>
</tbody>
</table>

**TABLE I**

Traces details for the three sets of data considered.

The third set of experiment comes from the Reality Mining project at MIT [18]. Data refers to a very long period (approximately one year), over which a set of students/researchers were tracked by means of mobile phones equipped with a Bluetooth interface. As for the Intel experiment, the Bluetooth device-discovery feature is exploited in order to detect the proximity of other Bluetooth-enabled devices. Each meeting is traced, and subsequently stored in a central repository for later processing.

In Table I, the details of the three experimentations are briefly summarized. It is worth noticing that the three experiments are referring to extremely different settings. As an example, Intel Exp 2 refers present the results derived from nodes meeting in a relatively closed environment, such as the one INFOCOM05, while the MIT Reality Mining project is considering the meetings of a nodes occurring at any time and place during the 1 year of experimentation. This results in extremely different meetings patterns, experimentation duration and nodes number participating in the measurements.

![Connectivity graphs for various values of T](image)

Fig. 2. \(T\)-tolerant connectivity graph for various values of \(T\), INTEL Exp3 trace.

As an example, in Fig. 2, the evolution of the \(T\)-tolerant connectivity graph for the Intel Exp3 trace is depicted. Nodes are assigned with a random position in the unit square. A link between any two nodes is drawn if and only if a contact between them was observed within the specified time window.
meetings pattern equal to the time duration of the experiment. This corresponds to assuming a periodicity of the traces, for the different nodes in the system. As it can be observed that after 2500 seconds a significant number of nodes already experienced more than one meeting.

For all the datasets considered, we took $T$ as the measurement times of the traces. It turned out, indeed, that taking long values of $T$ does not impact the EVC analysis, at least for the traces we are considering.

We started by considering EVC and the spreading process as a function of the initiator (infecting) node. For all the experiments, we first computed the EVC, as detailed in Sec. II. Then, we emulated the process of spreading (using the contacts in the corresponding trace file) starting from different “infecting” nodes. At time 0, one node is classified as “infectious”, and the remaining ones as “susceptibles”. Infectious nodes spread the epidemics at any contact with susceptible ones. Spreading ends once all the network is infected. In order to overcome the finiteness of the traces, if the complete spreading was not reached before the end of the trace, the same meetings pattern was applied. This corresponds to assuming a periodicity of the meetings pattern equal to the time duration of the experiment.

In Fig. 3, we reported the EVC in the case of the Intel Exp 3 trace, for the different nodes in the system. As it can be seen, the EVC is highly non-uniform. In Fig. 4 we plotted the corresponding fraction of infected nodes vs. time for an epidemics starting from node 1 ($EVC = 0.65$), node 12 ($EVC = 0.03$) and node 7 ($EVC = 0.142$). As expected, the EVC turns out to a significant measure of the ability of the node to initiate an epidemics. Please note, however, that the ability to spread an epidemics and the ability to initiate a spreading are, in general, different. For example, the curve corresponding to node 12 shows a sudden increase at about $0.85 \cdot 10^5$ seconds, where it meets the node with the highest EVC.

The same analysis is applied to the Intel Exp2 trace, with the epidemics starting from nodes 3 ($EVC = 0.66$), node 19 ($EVC = 0.07$) and node 2 ($EVC = 0.002$), respectively. The results are depicted in Fig. 5 and Fig. 6. Also in this case, centrality scores are highly non-uniform, and the graph shows that the choice of the infecting node has a remarkable impact on the speed at which an epidemic spreads in the system. As for the Intel Exp 3 trace, node 25, characterized by a low EVC value, at time $7 \cdot 10^4$ presents a sudden spreading increase derived from the meeting with a node with a high EVC value.

We have then considered the traces from the UMASS DieselNet project experiment. The results, in terms of eigenvector centrality and fraction of nodes infected with various infecting node, are reported in Fig. 7 and Fig. 8. It can be seen that the distribution is highly non-uniform, corresponding to a different ability of nodes of spreading an epidemic in the system. Differently from other experiments, in the UMASS Diesel trace the reported meetings occurred only among nodes participating to the experiment. As a result, the meetings pattern shows a higher regularity, and the EVC distribution is more uniform, if compared with the Intel Exp 1 and Intel Exp 2 EVC analysis. Correspondingly, to higher values of EVC correspond a higher capability of nodes both to initiate a spreading and to spread an epidemics. As an example, in Fig. 8 node 19 ($EVC=0.5$) not only presents the highest initial infection rate, but also infects the entire network in a short time, if compared with nodes with lower EVC values (i.e., node 2 and node 6).

In Fig. 9, Fig. 10, the EVC and the spreading power analysis has been extended to the MIT Reality Mining experiment. Also in this case, EVC distribution is highly non-uniform and this corresponds to faster or lower capacity of diffuse an epidemics within the nodes of the network. Node 3 presents the highest EVC value, and, correspondingly, a regular spreading pattern can be observed from Fig. 10. Conversely, node 2 presents an extremely low EVC score. This is reflected in an extremely low infection for the first $5 \cdot 10^5$ seconds, and a sudden and extremely fast diffusion afterwards. This behavior can be easily explained with node 2 meeting a node characterized by an extremely high value of EVC.

The outcomes are different for the Intel Exp3 trace. Indeed,\footnote{When leveraging on the bluetooth device-discovery capabilities for reporting neighboring nodes, any bluetooth-enabled device is reported.}
as it can be seen from the EVC, plotted in Fig. 11, just a fraction of the nodes in the system shows a non-negligible level of interactions. This can be due to the fact that all contacts with Bluetooth-enabled devices are recorded, not just with the other people in the experiment. A large fraction of the nodes appear for a limited number of times in the traces (in most cases, actually just once). The result is that the dependence on the EVC of the initiating node is only partial, in that it is valuable only for the nodes “truly” in the system. The other nodes appear mostly just once in the traces, so they cannot be infected until the very only meeting happens. For this reason, we decided not to report the graph of the fraction of infected nodes.

From all the considered real world deployments, we can reasonably conclude that EVC significantly represents the efficiency of nodes in spreading epidemics within a mobile network. This can be less evident, as in the case of nodes showing only a fast initiation of the spreading, or more evident, as in the case of nodes infecting the entire network in an extremely short time. The rational behind this behavior resides in the level of partition of the network. Nodes meeting on a more regular basis contribute to the initial boost of the spreading process, while nodes meeting only rarely (or only once) are responsible for the long tail of the epidemic spreading process. EVC impacts mostly the initial part of the spreading, and only partially the subsequent spreading of an epidemics.

**Region Analysis**

In the following, a simplified region analysis is conducted in the case of the UMass DieselNet project trace, with a time window of 8000 seconds. By following the steepest ascent rule [8] an ancestor is iteratively assigned to each node, until a local maximum is reached. The local maximum corresponds to a centre of the region [8]. From the conducted analysis, the network results to be partitioned in 2 distinct regions, node 1 being the peak of the first region with an EVC of 0.3822, and node 10 of the second one with an EVC of 0.5537. The first region consists of a total of two nodes, whereas the latter region consists of 13 nodes. The centres are shown as nodes having larger discs than the other nodes belonging to the regions. In Fig. 12, the resulting graph is depicted, with the corresponding EVC values. Regions centres are depicted with larger circles and the nodes belonging to the region of
node 10 are gridded, while the ones belonging to the region of node 1 in black. As it is intuitively clear, centre nodes are characterized by a high connectivity degree. Further, the two centres are not directly connected. Any path between the two centres has to go through another node.

Finally, in Fig. 13 and Fig. 14, the effect of the regions centre is highlighted in the case the UMass DieselNet project trace, with a time window of 8000 seconds. In Fig. 13, node 3 is starting the epidemics spreading. When node 10 becomes infected, it is possible to observe a significant boost in the spreading process. This effect is even more evident when the epidemics spreading reaches nodes 1: in less than 5000 seconds the remaining nodes of the network are infected. This is due to the well-connectedness of the region centre nodes. It is possible to observe a similar behavior in Fig. 14, where node 2 is the node initiating the epidemics spreading. Node 2 belongs to the region of node 1, and, therefore, node 1 is infected before node 10 (as opposed to the previous case).

V. CONCLUSIONS

The main contribution of this work is the extension of the eigen vector centrality principle to the case of a highly partitioned mobile network. By reflecting the well-connectness of a node, the eigen vector centrality significantly represents the ability of a node to spread epidemics in a highly mobile environment, such as the one considered in DTN application scenarios.

We have evaluated the nodes spread power over a wide range of real world deployments of disconnected mobile networks. Numerical results confirm the correspondence between the eigen vector centrality of a node, with its ability to spread an epidemic in a finite interval of time.

A research direction of interest is represented by the combination of the eigen vector centrality principle with relaying schemes (i.e., k-copy relaying mechanisms [3]). By having a measure of the spreading power of nodes, it becomes possible to efficiently tune the resources that are needed for achieving a predefined level of information diffusion in mobile disconnected networks.

REFERENCES

Fig. 11. Eigen Vector Centrality in the case of the INTEL Exp3 trace.

Fig. 12. Region analysis in the case of the UMASS trace, and time window of 8000 seconds.

Fig. 13. Fraction of infected nodes, with a time window of 8000 seconds, and node 3 starting the epidemics spreading.

Fig. 14. Fraction of infected nodes, with a time window of 8000 seconds, and node 2 starting the epidemics spreading.