Characterizing the Topology of an Urban Wireless Sensor Network for Road Traffic Management

Sébastien Faye*, Claude Chaudet†

***Abstract*—In a near future, wireless networks will be one of the key technologies for road traffic management in smart cities. Vehicles and dedicated roadside units should be interconnected through wireless technologies such as IEEE 802.11p (WAVE). Traffic light and road signs may also take their place in this architecture, forming a large-scale network of small devices that report measurements, take orders from a control center, and are able to take decisions autonomously based on their local perception. Such a network shares many similarities with classical wireless sensor and actuator networks, starting with its distributed organization and with the role of the control center. However, its topology, and subsequently the appropriate selection of protocols and algorithms, will be strongly influenced by each city's characteristics. In this article, we characterize and discuss probable topologies of these networks. The aim of this work is to provide network models that can be used to evaluate protocols and algorithms using realistic scenarios in place of generic random graphs. We deploy such networks over 52 city maps extracted from OpenStreetMap and characterize the resulting graphs, with a particular focus on connectivity aspects (degree distribution and connected components). The tools, the complete datasets, OMNeT++ network models are available freely online.**

***Index Terms*—Smart Cities, Wireless Sensor Networks, Network Topology, Graphs**

I. Introduction

Operators rely more and more on digital systems to monitor road traffic. Intelligent Transportation Systems (ITS) are now able to control traffic lights, limit congestion, prevent accidents and reduce pollution or noise levels. In this context, the success of today's embedded systems allows deploying a dense network of detectors and actuators that communicate using wireless communications [1], [2], [3]. Tiny devices can be installed at traffic lights, or on urban lighting systems to measure carbon dioxide, micro-particle or noise levels, or to count vehicles using a magnetometer or a camera. Using wireless transmissions instead of optical fibers reduces installation costs and facilitates interaction with vehicles. These devices are powerful enough to auto-organize, report measurements to centralized acquisition and control software such as SCOOT [4] or SCATS [5] and receive global policies in return. Deploying such a large-scale network would provide a fixed infrastructure, fostering the development of vehicular applications that require a minimal amount of users to form an infrastructure. However, when the traffic load is high, a small event can easily and rapidly escalade into a severe congestion [6] and communicating with a central decision point may not be the most efficient solution [7]. The time required to communicate with a central entity may impede the development of responsive applications such as accident or congestion detection. A decentralized system that works locally naturally alleviates this problem. Taking advantage of the distributed computing results, such devices can easily communicate together and rapidly adapt the traffic light plans to solve a situation [3]. This type of architecture can make intersections or urban areas totally autonomous and independent of any central entity, in addition to increase fault tolerance. However, extensive and realistic evaluations need to be realized before convincing urban planners of the benefit of decentralized systems.

This paper studies and characterizes the plausible shape of a network formed by static wireless devices deployed at every intersection of a real city. If such networks are often limited to the most congested zones or to the largest streets, we believe that a citywide deployment makes sense, as it allows building efficient and reactive traffic management strategies. Traffic from congested areas can be, for example, offloaded to quieter zones. However, this process should be controlled to be efficient. Secondary streets should be monitored to detect small events that can often escalate to blocking situations and provide a fast and appropriate reaction. The huge amount of research in ad-hoc, mesh and sensor networks has shown that the network topology has a strong effect on the network performance, its reliability and its adaptation capacities [8], [9], [10], [11]. Selecting the appropriate set of algorithms and protocols requires a full characterization of the scenario and the network topology.

Based on a few deployment strategies that we explain in Sec. III, we derive graph models for these topologies that better reflect real topologies than the generic random graph models. These communication graphs result from the sensors deployment over 52 city maps extracted from *OpenStreetMap*. The tools used to generate the topologies as well as the whole set of results and additional conclusions are available online (Sec. III-C). We then analyze the resulting graphs structural properties in terms of local connectivity, and discuss the networking aspects in Sec. IV.

* Interdisciplinary Centre for Security, Reliability and Trust, University of Luxembourg, 4 rue Alphonse Weicker, L-2721 Luxembourg (e-mail: *sebastien.faye@uni.lu*).

† Institut Mines-Telecom, Telecom ParisTech, CNRS LTCI UMR 5141, Paris, France (e-mail: *claude.chaudet@telecom-paristech.fr*).

II. Related Works

A. Deployment

Using embedded devices to help managing smart cities is not a novel idea. Press-covered research results show the interest of fine-grained traffic monitoring for suppressing instability in traffic flows [6] and for reducing the congestion level. The ramp metering systems that have been deployed by some cities show that an active management of traffic lights could reduce drastically the traffic jams, even though the Minneapolis ramp meters were highly contested by users who had the *feeling* that waiting times increased.

Several projects and initiatives have reached an experimental phase and a few medium-scale deployments have begun. Sensor networks experimental platforms are legion today, but most of them are limited to one or a few buildings (e.g., Motescope [12] or FlockLab [13]). In contrast, CitySense [14] is an urban wireless network testbed deployed all over the city of Cambridge (MA, USA), forming a mesh network. It is composed of 100 Linux-based computers that can be programmed directly by end users. Even though the primary focus was to foster mesh networks applications development, nodes have been augmented with environmental and pollution sensors.

Corredor *et al.* [15] look at the deployment of magnetometers for monitoring road traffic over smart highways. They propose to deploy such sensors on every lane to maximize vehicles detection probability and couple the sensors with roadside units to solve connectivity problems. Hu *et al.* [16] proposes to deploy sensors across the second ring road of Beijing (China) for road traffic monitoring. They influence the deployment so that the resulting topology forms a small world graph to take advantage of this type of structures, by optimizing transmission radiuses of the nodes and refining the location of high coverage nodes using an evolutionary algorithm. CitySee [17] is a project to deploy a sensor network in the city of Wuxi (China) to measure the carbon dioxide level in real-time. The paper models the deployment issue as a relay node placement problem and evaluates the number of additional nodes deployed for connectivity purposes.

Some authors in the literature define the deployment of ITS, such as traffic light control algorithms that act locally on each intersection of a road infrastructure [1], [2], [18]. Their algorithms are based on sensors deployed at an intersection for the purpose of calculating a timed sequence of green lights corresponding to the level of traffic. By defining the roles and hierarchy of the sensors, [18] uses communications between the adjacent intersections to create green waves (paths of successive green lights).

B. Impact of topology

All these papers propose different deployment strategies, and the resulting connectivity graphs are expected to be slightly different. In the literature, it is commonly assumed that city maps are scale-free networks. Besides, the complex networks analysis methods that are widely used in social networks analysis are also applied in urban networks [19], [20], [21]. However, the topology of the communication network deployed over a city infrastructure depends on the deployment method and this topology has a strong effect on the network protocols performance at all levels of the communication process.

Ishizuka and Aida [8] examine the effect of sensor topology on fault tolerance and event-detection probability. In particular, their simulations show that the initial placement of the sensors has a significant effect on the reliability of the network. Vassiliou and Sergiou [9] study the performance of algorithms that control congestion for wireless sensor networks on the same topologies as Ishizuka and Aida [8]. They show that transmission delays or delivery rates, which directly depend on the network topology, strongly affect the congestion control algorithms. Puccinelli *et al.* [10] evaluate the impact of the topology on the data collection of a sensor network using experimental results. They conclude that topology must be taken into consideration for a protocol to be fully evaluated. Ducrocq *et al.* [11] evaluate the impact of network topology on geographic routing. Notably, they show that different topologies can lead to a difference of around 25% on the delivery rate and the average length of a route, and up to 100% on the overall cost of transmission.

Yet, very few contributions really tried to propose realistic models of large-scale urban sensor networks. Naboulsi and Fiore [22] examine the topology of a vehicular network, i.e. a mobile network, in the city of Cologne (Germany). The authors show the weaknesses that vehicular protocols may encounter: mobility is perceived as an additional constraint, creating a very volatile and fragmented network. However, no contribution to our knowledge, has characterized the topology of a fixed distributed network of sensors and actuators that would be deployed and managed by the city itself, even though the applications of such networks for traffic lights and adaptive speed limits management is obvious.

III. Deploying Sensor Nodes in Cities

A. Deployment strategies

There are several strategies to deploy sensors over an urban road network to count vehicles, as illustrated on Fig. 1. **(1)** a single sensor per intersection, as shown by the blue dot on Fig. 1(a), e.g. using a fisheye camera. **(2)** one sensor on each *road* (green dots on Fig. 1(b)), e.g. using overhead cameras capturing multiple lanes simultaneously, backed up by video analysis software. **(3)** one sensor at the end of each *incoming* lane (yellow dots on Fig. 1(c)), allowing a precise vision of the vehicles flow. This strategy is a minimum requirement for measuring average vehicle flow with magnetometer-type sensors [23]. **(4)** two sensors per lane (red dots on Fig. 1(d)): one recording the arrivals and the other capturing the departure process [3].

All these strategies are plausible, even though they provide different levels of accuracy. In the rest of this article, the results presented assume that the sensors are deployed individually on each lane, which corresponds to the third scenario (Fig. 1(c)). We focus on this strategy for two main reasons. **(1)** We choose lanes rather than roads (green dots) or intersections (blue dot) because we have in mind magnetometer-like sensors instead

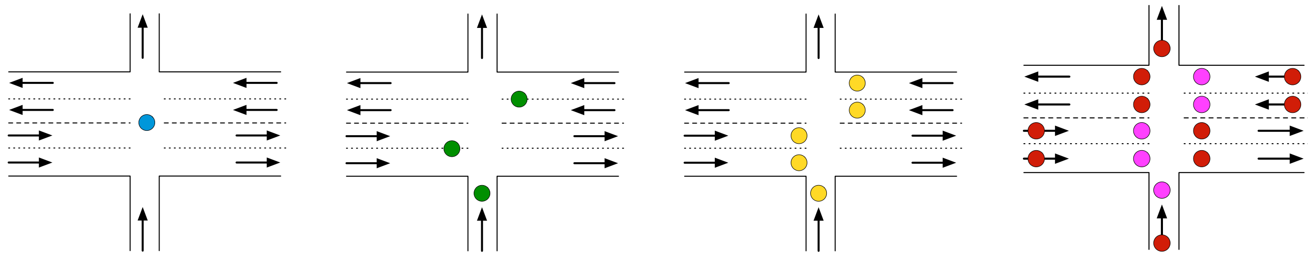

Fig. 1. Sensors deployment strategies on an intersection between a major road (4 lanes) and a minor street (1 lane, 1 way).

of cameras that require special mounts and increased network capacity to transmit video flows, or more CPU to analyze it locally. **(2)** We deploy one sensor per-lane instead of two because it is a minimum requirement to implement an ITS, as the sensor can detect one vehicle on each lane, halving deployment costs. However, results obtained for each strategy are available online (Sec. III-C).

B. Creating the connectivity graph

In this section, we detail the method we used to build the graph $G = (N, E)$ that we will analyze in the rest of this article. Let us consider a given city map, extracted from a public database such as OpenStreetMap. This map gives us the GPS coordinates of each intersection, as well of the characteristics of the roads that connect these intersections. A given deployment method will result in the creation of a set of *nodes* N that possess geographic coordinates. To create the associated undirected edge set E, we confront the Euclidean distances between each couple of sensors to a distance modeling the transmission range of the nodes. To this extent, we associate to each possible edge, $\{(i, j, \delta)\} \in E$, a normalized weight $\delta \in]0 : 1]$ that models the decrease of the quality of the wireless link with the distance. In our current setup, this weight is calculated based on the *Sensys Networks VSN240* sensors[1] model, which are used on roads all around the world and can be deployed densely [24]. These nodes use a nominal output power of $0\ dBm$ and have a receiver sensitivity of $-95\ dBm$ in the 2.4 GHz band. We confront these values to a simplified propagation model that corresponds to a 2.4 GHz IEEE 802.15.4 network interface ([25], [26]). This model defines the path loss (in dB) across a distance of d meters as follows:

$$PL(d) = \begin{cases} 40.2 + 20\log_{10}(d), & 0.5m \leq d \leq 8m \\ 58.5 + 33\log_{10}(d/8), & d > 8m \end{cases} \quad (1)$$

The weight of an edge is a normalization of $PL(d)$ using $1 - \frac{PL(d) - PL(0.5)}{PL_{max} - PL(0.5)}$, where $PL(0.5)$ is the minimum value of the path loss according to formula (1), and PL_{max} its maximum value, which depends on the receiver characteristics. An edge exists if and only if its weight is positive (i.e. $PL(d) < PL_{max}$). This model, which simply defines a transmission range at this level of analysis, should fit most technologies that operate in the S-band (2 GHz to 4 GHz) and can be adapted to other narrow frequency bands such as the 5.9 GHz band utilized by IEEE 802.11p (WAVE). Note that the resulting graphs are different from classic urban street network graphs, as the wireless links do not follow the roads and multiple nodes are located at each intersection. Besides, we can expect less directed edges in a connectivity graph (asymmetric link) than in an urban network (one-way-street).

[1]http://www.sensysnetworks.com/products/sensor/

C. Creation of the scenarios database

We applied the graph creation method described in section III-A on a set of 52 city maps extracted from *BBBike.org*[2], a service that offers to retrieve *OpenStreetMap*[3] maps data from more than 200 cities and region worldwide. These maps have gone through several modifications, thanks to crowdsourcing, and are now accurate enough for navigation software [27]. We remove irrelevant map elements (e.g., bike lanes, pedestrian areas) with *NETCONVERT*, a tool provided by the SUMO microscopic traffic flow simulator [28]. We also removed minor roads (e.g. residential, non-motorized) and kept only main and secondary streets[4].

The full dataset comprising the 52 city maps and the results are available online[5], as well as the scripts to generate the graph. These scripts invoke the different tools in sequence with configurable parameter (path-loss model, deployment method, etc.). They can be executed remotely through a web interface, or downloaded from the same address under the LGPL license. The SUMO and Omnet++ models are also available online, allowing joint simulation of the traffic and communication networks.

In the rest of this article, we use 6 representative cities to illustrate our analysis, selected based on three properties. *New Orleans* and *Beirut*, which have respectively the largest and the smallest covered area. *Miami* and *Cusco*, which are respectively the densest and the sparsest networks in our dataset, as illustrated in Figure 2. Finally, *Madrid* and *Paris*, which have an average size and density, and an interesting morphology as we can see in our full result dataset.

[2]http://download.bbbike.org/osm/
[3]http://www.openstreetmap.org/
[4]See definition in http://wiki.openstreetmap.org/wiki/Key:highway
[5]**http://g.sfaye.com/**

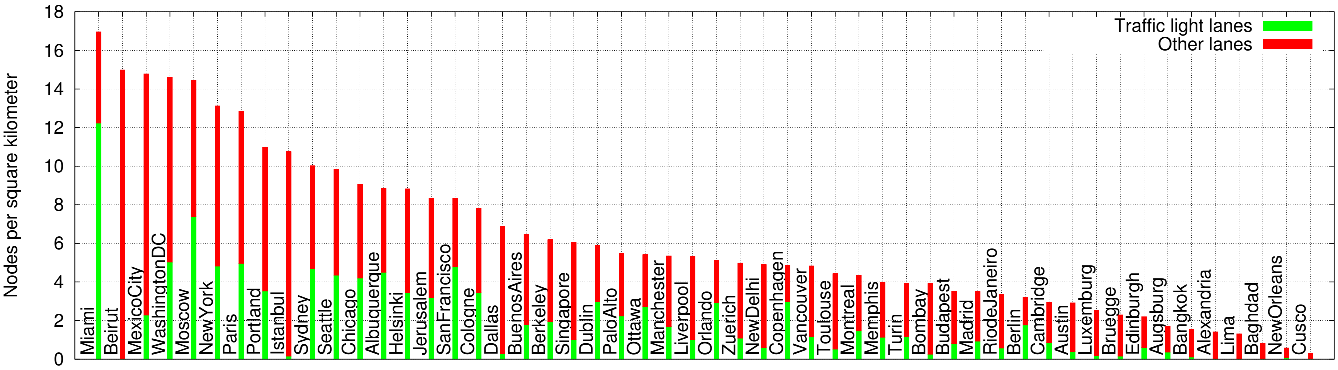

Fig. 2. Networks density (nodes per square kilometer) for the 52 cities that compose our dataset

IV. Connectivity graphs analysis

In this section, we study the properties of the resulting graphs, focusing on their degree distribution to see if they correspond to a classical random graph model. We then discuss on their partitioning and examine the resulting connected components.

A. *Degree distribution analysis*

Figure 3 shows the average node degree for each network, i.e. the average number of nodes that are within transmission range of an arbitrary node. In terms of networking, node degree represents the number of contenders each node has to compete with for accessing the wireless channel. As a node has to share the channel bandwidth with all its neighbors, network planning should aim for a relatively low degree. Yet, a too small value is not desirable, as a fair degree offers path diversity and redundancy.

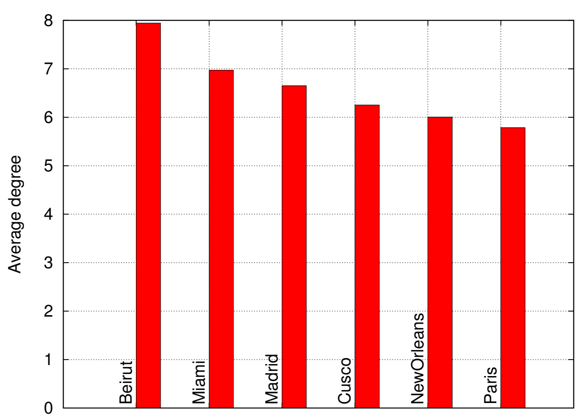

Fig. 3. Average node degree

These results shows that all graphs have a similar average degree that lies between 5 and 8 neighbors. Given the considerable amount of performance evaluations realized on various wireless technologies and considering the technological choices that standards (Bluetooth, Zigbee, etc.) usually make, this fits quite well the classical use case of today's wireless standards. Cities like Beirut, whose road network is relatively uniform, have a higher average degree than other cities like Paris, for example, which have a wide suburban area.

Beyond the average value, the whole degree distribution is a classical measure to characterize large graphs. From our results, we can notice that degree distributions cannot be fitted by Poisson distributions, as the empirical average and standard deviation are very different in all of them. They do not correspond to a power law distribution either, as the log-log representation of their degree distribution is far from linear. Fig 4 shows the quantile vs. quantile plot of the empirical distributions with gamma distributions whose *scale* parameter (θ) is estimated as the ratio between the empirical degree variance (σ^2) and the average empirical degree (μ). The *shape* parameter (k) is the ratio between the empirical average and the scale parameter: $\theta = \sigma^2/\mu$ and $k = \mu/\theta$.

Fig 4 shows that the approximation is reasonable and only deviates for high degree nodes. Figure 5 represents, as an additional example, the empirical degree distribution measured on Paris and the fitted gamma distribution (black curve ; $\theta = 2.558382$ and $k = 2.26065$).

B. *Suitability of classical random graphs models*

As the degrees tend to follow a gamma distribution, none of the state of the art random graphs model really fits this type of networks. The model from Gilbert [29] produces graph whose degree distribution is binomial. Erdös and Rényi [30] model generates graphs whose degree distribution follows a Poisson distribution, as well as the random geometric graph model [31], which is classically used to generate random wireless networks. The preferential attachment method proposed by Barabasi and Albert [32], as well as the Watts and Strogatz model [33] both produce scale-free networks whose degree distribution follows a power law.

It is possible to generate graphs that match our deployments. The experimenter should first decide of the type of city he wishes to generate and decide of the shape and scale parameters of the gamma distribution. Smaller shape values shift the distribution towards low degrees and hence model cities in which intersections are far away from each other. The scale parameter defines the height of the peak and hence models how uniform the degrees will be. It accounts to some

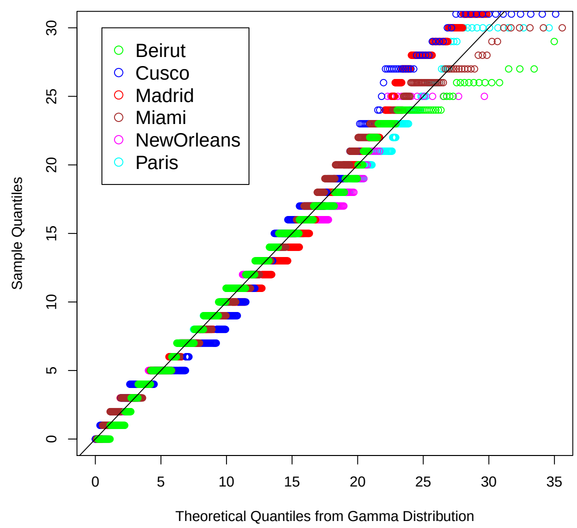

Fig. 4. Quantile-Quantile Plot of Degree distributions vs. Gamma distributions

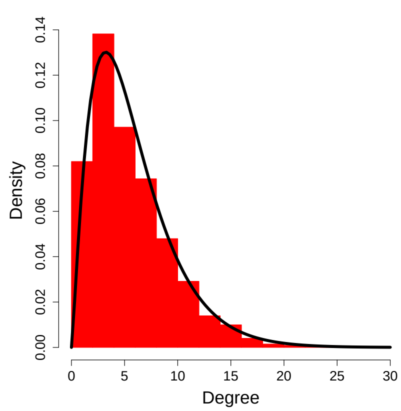

Fig. 5. Paris. Empirical and fitted degree distributions

extent for the regularity of the distances between the intersections. The Molloy and Reed method [34] allows creating graphs with an arbitrary degree distribution, including gamma distributions. However, it produces scale-free graphs. Each node can communicate with any other node in the network, and this tends to create fewer connected components than can subsequently be observed. One solution would be to adapt the Molloy and Reed method to the context of geometric graphs rather than using traditional graphs. Apart from being based on a degrees sequence that respects a gamma distribution, each node would be defined by a geographic location. This would imply the need for a dimension parameter, so that the placement of the nodes respects the schemes we describe in our dataset. The idea we have in mind has two stages. First, creating nodes based on the distribution of the center of gravity of connected components. Secondly, changing these nodes to connected components, formed with new nodes that follow a known degree distribution.

C. A brief review of global connectivity

While the degree distribution accounts for local connectivity, the number of *connected components* in the resulting graphs evaluates the global connectivity (i.e. partitioning) of the networks. A connected component models a group of nodes that are connected together, but disconnected from the rest of the network because of the long distance with the other groups of nodes. In this case, each partition would be autonomous and need to be explicitly connected to the control center, either by an optical fiber, or by a wireless or a cellular network. Figure 6 shows the number of connected components in the different networks (red bars). This number depends directly on the dimension of the different networks as well as on the number of nodes. Paris has more than 5 500 components for 29 000 nodes, for example. This means that the network, without additional relays, is composed of many areas and hence has limited interaction possibilities. Green bars describe the number of *biconnected components* in each network, i.e. connected components in which there are at least two node-disjoint paths between each couple of nodes. Figure 6 also shows that few connected components are not biconnected, indicating that relatively few additional nodes need to be deployed to comply with the classical N-1 reliability criterion (i.e., the loss of any single element does not break a connected component in two).

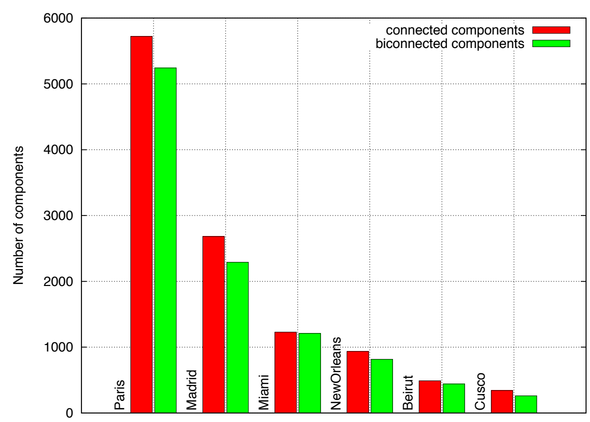

Fig. 6. Number of connected and bi-connected components

Network partitioning is not an issue *per se*, as the components can also be interconnected together by a cellular network or by a metropolitan wired network. However, the number of independent network components should remain reasonable to limit the backbone complexity. Yet, merging connected components requires deploying additional nodes that act as relays and do not need to measure traffic. There is therefore a compromise between the number of additional relays to deploy and the number of connected components. Figure 7 shows the CDF of the distance between a component and its neighbor component. To identify the closest components, we first compute the coordinates of the centroid of each connected component. This produces a set of points in the plan and we build the Voronoi diagram of this set of points. A Voronoi diagram separates the plan in zones centered on each node. A zone is composed of all the points that are closer to the

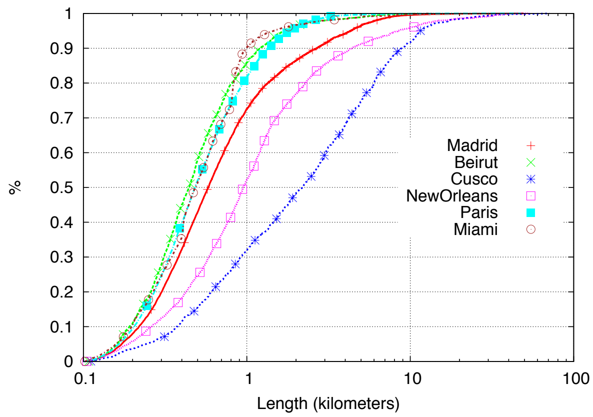

Fig. 7. CDF of the distance between close connected components

central node than any other node. We then consider that two components are neighbors if their Voronoi cells have a common frontier. Figure 7 shows that a few components are very far from the rest of the network, but that most components are relatively close to each other, which indicates that reducing the number of components by inserting intermediate relays should be efficient. Paris has, for example, 80 % of connected components that are separated by less than 1 km, which should be easily coverable with intermediate nodes or complementary networks.

V. Conclusions and Future Works

In this paper, we examined and characterized a strategy to deploy a sensor network at the intersections of various cities. We present the graph generation method we used, that is simply based on operational constraints, and analyze the resulting graphs in terms of local and global connectivity. The usual random graphs models fail to represent these networks whose degree distribution fits a gamma distribution. The Molloy and Reed method could be modified to generate more accurate graphs. Examining the partitioning in connected components, we show that the resulting graph is highly disconnected and comprises up to 25 % of isolated nodes.

Extended results, available online (Sec. III-C), show that the network indeed presents a good redundancy level within connected components. Besides, the average diameter of each connected component is generally low and only a moderate proportion relay nodes is required to let the maximum connected component cover most of the urban area.

The effect on various network protocols and algorithms remains to be evaluated, for example through simulation. However, the conclusions that we draw in this article should help selecting the most appropriate protocols for this class of scenarios. In future works, we intend on studying formally correlations between geographic parameters and network graph parameters to improve the graph generation method we sketched. We also intend bringing the analysis to the networking level by comparing state of the art protocols and algorithms using simulation tools. Finally, in order to consider complex elements of urban areas (e.g., buildings), it would be interesting to use a more complex propagation model and therefore more parameters in our graph creation method.

References

[1] K. M. Yousef, J. N. Al-Karaki, and A. M. Shatnawi, “Intelligent traffic light flow control system using wireless sensors networks,” *Journal of Information Science and Engineering*, vol. 26, no. 3, May 2010.

[2] F. Zou, B. Yang, and Y. Cao, “Traffic light control for a single intersection based on wireless sensor network,” in *9th International Conference on Electronic Measurement & Instruments (ICEMI 2009)*, Beijing, China, Aug. 2009.

[3] S. Faye, C. Chaudet, and I. Demeure, “A distributed algorithm for multiple intersections adaptive traffic lights control using a wireless sensor networks,” in *UrbaNe Workshop (held in conjunction with ACM CoNEXT 2012)*, Nice, France, Dec. 2012.

[4] D. Robertson and R. Bretherton, “Optimizing networks of traffic signals in real time-the scoot method,” *IEEE Transactions on Vehicular Technology*, vol. 40, no. 1, Feb. 1991.

[5] A. Sims and K. Dobinson, “The sydney coordinated adaptive traffic (scat) system philosophy and benefits,” *IEEE Transactions on Vehicular Technology*, vol. 29, no. 2, May 1980.

[6] B. Horn, “Suppressing traffic flow instabilities,” in *IEEE Intelligent Transportation Systems Conference (ITSC 2013)*, Den Haag, Netherlands, Oct. 2013.

[7] S. Lämmer and D. Helbing, “Self-control of traffic lights and vehicle flows in urban road networks,” *Journal of Statistical Mechanics: Theory and Experiment*, vol. 2008, no. 04, p. P04019, 2008.

[8] M. Ishizuka and M. Aida, “Performance study of node placement in sensor networks,” in *24th International Conference on Distributed Computing Systems Workshops (ICDCS)*, Tokyo, Japan, 2004.

[9] V. Vassiliou and C. Sergiou, “Performance study of node placement for congestion control in wireless sensor networks,” in *WSN Workshop, held in conjunction with NTMS 2009*, 2009.

[10] D. Puccinelli, O. Gnawali, S. Yoon, S. Santini, U. Colesanti, S. Giordano, and L. Guibas, “The impact of network topology on collection performance,” in *8th European conference on Wireless sensor networks*, 2011.

[11] T. Ducrocq, M. Hauspie, N. Mitton, and S. Pizzi, “On the Impact of Network Topology on Wireless Sensor Networks Performances Illustration with Geographic Routing,” in *International Workshop on the Performance Analysis and Enhancement of Wireless Networks (PAEWN)*, Victoria, Canada, May 2014. [Online]. Available: http://hal.inria.fr/hal-00959921

[12] UC Berkeley, “Motescope.” [Online]. Available: http://smote.cs.berkeley.edu/motescope/

[13] R. Lim, F. Ferrari, M. Zimmerling, C. Walser, P. Sommer, and J. Beutel, “Flocklab: A testbed for distributed, synchronized tracing and profiling of wireless embedded systems,” in *Proceedings of the 12th international conference on Information processing in sensor networks*. ACM, 2013, pp. 153–166.

[14] R. N. Murty, G. Mainland, I. Rose, A. R. Chowdhury, A. Gosain, J. Bers, and M. Welsh, “Citysense: An urban-scale wireless sensor network and testbed,” in *Technologies for Homeland Security, 2008 IEEE Conference on*, 2008.

[15] I. Corredor, A. García, J. Martínez, and P. López, “Wireless sensor network-based system for measuring and monitoring road traffic,” in *6th Collaborative Electronic Communications and eCommerce Technology and Research (CollECTeR 2008)*, Madrid, Spain, Jun. 2008.

[16] J. Hu, J. Song, M. Zhang, and X. Kang, “Topology optimization for urban traffic sensor network,” *Tsinghua Science & Technology*, vol. 13, no. 2, 2008.

[17] X. Mao, X. Miao, Y. He, X.-Y. Li, and Y. Liu, “CitySee: Urban CO2 Monitoring with Sensors,” in *Infocom*, 2012.

[18] S. Faye, C. Chaudet, and I. Demeure, “Influence of radio communications on multiple intersection control by a wireless sensor network,” in *ITS Telecommunications (ITST), 2013 13th International Conference on*, 2013.

[19] S. Porta, P. Crucitti, and V. Latora, “The network analysis of urban streets: a primal approach,” *Environment and Planning B: Planning and Design*, vol. 33, 2006.

[20] P. Crucitti, V. Latora, and S. Porta, “Centrality measures in spatial networks of urban streets,” *Physical Review E*, vol. 73, no. 3, 2006.

[21] S. Porta, P. Crucitti, and V. Latora, “The network analysis of urban streets: a dual approach,” *Physica A: Statistical Mechanics and its Applications*, vol. 369, no. 2, 2006.

[22] D. Naboulsi and M. Fiore, "On the instantaneous topology of a large-scale urban vehicular network: the cologne case," in *Proceedings of the fourteenth ACM international symposium on Mobile ad hoc networking and computing*, 2013.
[23] M. Tubaishat, Q. Qi, Y. Shang, and H. Shi, "Wireless sensor-based traffic light control," in *5th IEEE Conference on Consumer Communications and Networking (CCNC 2008)*, Las Vegas, USA, Feb. 2008.
[24] A. Haoui, R. Kavaler, and P. Varaiya, "Wireless magnetic sensors for traffic surveillance," *Transportation Research Part C: Emerging Technologies*, vol. 16, no. 3, 2008.
[25] "Coexistence of wireless personal area networks with other wireless devices operating in unlicensed frequency bands," *IEEE Standard 802.15.2-2003*, 2003.
[26] K. Marquess, "Physical model sub-group discussion and questions," *IEEE 802.15/138R0*, 1999.
[27] M. Haklay, "How good is volunteered geographical information? a comparative study of openstreetmap and ordnance survey datasets," *Environment and planning. B, Planning & design*, vol. 37, no. 4, 2010.
[28] D. Krajzewicz, J. Erdmann, M. Behrisch, and L. Bieker, "Recent development and applications of SUMO - Simulation of Urban MObility," *International Journal On Advances in Systems and Measurements*, vol. 5, no. 3&4, December 2012. [Online]. Available: http://elib.dlr.de/80483/
[29] E. N. Gilbert, "Random graphs," *Annals of Mathematical Statistics*, vol. 30, 1959.
[30] P. Erdös and A. Rényi, "On random graphs i," *Publicationes Mathematicae*, vol. 6, 1959.
[31] M. Penrose, *Random Geometric Graphs*. Oxford Studies in Probability, 2003.
[32] A.-L. Barabási and R. Albert, "Emergence of scaling in random networks," *Science*, vol. 286, no. 5439, Oct. 1999.
[33] D. J. Watts and S. H. Strogatz, "Collective dynamics of 'small-world' networks," *Nature*, vol. 393, no. 6684, 1998.
[34] M. Molloy and B. Reed, "A critical point for random graphs with a given degree sequence," *Random Structures and Algorithms*, vol. 6, no. 2-3, 1995.

Sébastien Faye obtained his PhD degree from Télécom ParisTech (Paris, France) in 2014. After completing his Master, Sbastien carried out a number of studies on wireless sensor networks and the security mechanisms they offer. During his Ph.D, he studied ways in which such distributed systems can manage intelligent transportation systems, investigating their deployment and performance in the area of traffic light management. Since 2014, he is Research Associate at the University of Luxembourg (SnT). His research interests are wireless sensor networks, hierarchy and partitioning, intelligent transportation systems.

Claude Chaudet obtained his Ph.D degree in computer science in 2004 from Insa de Lyon (Lyon, France). He is Associate Professor at Télécom ParisTech (Paris, France) since 2005 and a member of the LINCS laboratory. His research mainly focuses on distributed networks formed spontaneously by embedded devices. He is involved in various academic and industrial collaborations on network modeling and performance evaluation, on applications design, and on security and privacy issues.