Topology Characterization for Position-based Wireless Network Topology Generators

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***Abstract*—Topologies are usually characterized in terms of their network graph; usually by investigating their degree frequency, rank/degree, or hop/count distributions. Wireless network simulation, on the other hand, typically does not use network graphs. Instead, in most wireless simulations, nodes are first positioned on the terrain based on some positioning algorithm and then a radio propagation model is used to determine connectivity dynamically at simulation run-time. For this use-case, methods to characterize network topology based solely on the spacial positions of the nodes on the terrain are necessary. We propose several metrics and show how they can be used to evaluate position-based topologies: the nearest neighbor distance distribution, a threshold and a probabilistic node degree measure, and the application of an inhomogeneity measure for spatial distributions.**

I. Introduction

Computer networks are usually characterized by their graph properties, thus, a network consists of vertices representing network nodes and directed or undirected edges representing connectivity. Such networks can be characterized by density, average degree, diameter, and clustering coefficient. These measures have been successfully applied to describe mostly static, wirebound networks, such as generated random networks with Internet-like characteristics [1]. Borschbach and Lippe presented a model of homogeneity based on a graph theoretical model for ad-hoc networks [2].

However, wireless network simulations typically compute a network by first using a spatial model to place the nodes, followed by calculating the connection probability with a radio propagation model [3], [4]. The connectivity of two nodes depends on the signal to noise ratio at the receiving node, which is a function of path loss, shadowing and fading models, and the current transmission power of nearby nodes. Connectivity models often are probabilistic, thus yielding an expected reception probability for any given link. Over time the connections in a network are typically dynamic.

Additionally, for real-world wireless networks, a graph-based model is often unavailable or hard to obtain unlike node positions and their transmission properties. Thus, there is a need to assess network properties from node positions in order to characterize and compare real-world networks to artificial network models generated by topology generators such as [5]–[7] or the map-based generator MAGANET [8] or the approach using a random topology generator based on an Erdos-Renyi model and a topology generator based on a SNAP (Stanford Network Analysis Project) network dataset proposed by Nandi [9] for Software Defined Network testing.

To characterize wireless networks, we suggest an alternative approach to using graph-theoretical network properties alone. This paper investigates different approaches to characterize network topologies based on the spatial distribution of nodes. In Section II, different metrics for this purpose are identified, which are applied to characterize four real-world distributions of urban rooftop networks and compared with an artificially generated topology model in Section III. The effectiveness of the approach is discussed in the conclusion in Section IV.

II. Metrics

In the following, we introduce four useful metrics for the characterization of position-based topologies, namely: nearest neighbor distance distribution, a probabilistic and a threshold node degree measure based on the propagation model used in the simulation, and the application of an inhomogeneity measure for spatial distributions.

A. Nearest Neighbor Distance Distribution

To be connected, every node in the network has to be connected to at least one neighbor and there has to be a path between any pair of nodes. Based on the first property, each node n_i must have at least one neighbor n_b where the distance d between them is within the communications range: $d(n_i, n_b) \leq d_{\mathrm{comm}}$

Assuming a propagation model based on node distance (which is what is typically used in wireless simulation models), it therefore makes sense to investigate the distance distribution of the nearest neighbors (NNB).

Nearest neighbor distances shorter than the communications range are a necessary (but in real-world networks not sufficient) criterion for connectivity in the network. If the distance between two nodes is larger than the communications range then communication between these two nodes in a radio network is unlikely. Therefore, a network in which a significant fraction of the nearest neighbor distances are above the communications range has a high probability of being disconnected.

B. Propagation Model Based Node Degrees

Network generators based on the degree distribution follow the implicit assumption that matching a certain local property like the degree distribution produces a network resembling the original structure. Tangmunarunkit et al. have shown that such an approach can accurately capture the large-scale structure of measured topologies [10].

Before a node degree can be calculated, a propagation model has to be applied to the position-based topology to transform the distance matrix into a connection probability (CP) matrix. Once the CP matrix has been calculated, there are two ways to interpret these probabilities as a node degree:

1) **"threshold" degree** For this, a connection probability threshold is chosen that is deemed "good enough" for the intended higher layer protocol(s) and traffic. All links with a connection probability higher than or equal to the threshold are counted towards the degree of the node while all links with a connection probability lower than the threshold are ignored. This results in integer values for the node degrees.
2) **"probabilistic" degree** The degree of a node is calculated as the sum of the connection probabilities of all its links: $\deg_p = \sum_i \mathrm{CP}(l_i)$ eg. a node with two links l_1, l_2 with connection probabilities of $\mathrm{CP}(l_1) = 0.95$ and $\mathrm{CP}(l_2) = 0.90$ would have a probabilistic degree of $\deg_p = 1.85$.

C. Inhomogeneity Factor

A different way to look at the distribution properties of wireless network nodes is to look at node density and the inhomogeneity of the node distribution in the spatial domain. The node density in node per area unit is straightforward to calculate. To measure inhomogeneity, we are aiming at an objective quantitative measure of inhomogeneity. Schilcher et al. define three properties for such a measure: (i) provide values in a defined range between 0 and 1, (ii) being independent of network scale, and (iii) being unaffected by linear operations such as shifting, mirroring or rotating [11], [12]. They propose an algorithm for calculating an inhomogeneity measure, which fulfils these requirements. We use this metric as one way of characterizing position-based wireless networks. The algorithm involves a recursive segmentation of the area, where the recursion depth depends mainly on the number of involved nodes. The result, called h is near zero for regularly spaced node deployments and approaches a value of one for highly inhomogeneous networks. Thus, a high value indicates a strongly clustered network.

III. Application to Real-World Examples

We consider rooftop-to-rooftop wireless mesh networks using commercial off-the-shelf WiFi technology as our real-world examples, but the metrics can be applied to other wireless mesh networks such as sensor networks as well.

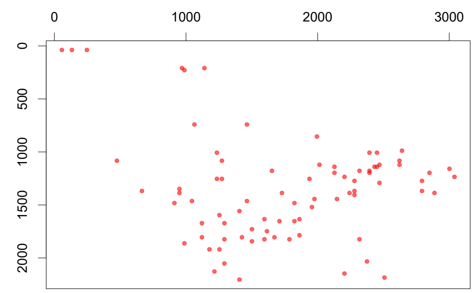

Fig. 1. Real-World Node Positions: MIT Rooftop network (scale in meters).

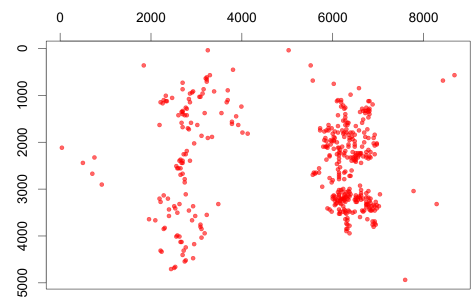

Fig. 2. Real-World Node Positions: Leipzig (scale in meters).

Figures 1, 2, 3, and 4 show the node positions of real-world wireless mesh networks from the MIT Rooftop network [13], Leipzig [14], Vienna [15], and Berlin [16]. For each of these networks we got the node positions from street maps on the respective project homepages.

As can be seen, these topologies exhibit obvious clustering and are not uniformly distributed on the terrain. While there exists work using random geometric graphs as models for wireless multi-hop networks such as [17], these results rely on the property of random geometric graphs that the nodes be distributed *uniformly*. Since this is clearly not the case for our real-world examples, we therefore investigate these networks experimentally using the metrics proposed above.

The most interesting application of such metrics, though, is to judge whether any artificially created topologies that are used in a simulation actually resemble the features of the real-world networks they are supposed to model. Consider the following example: assume we want to do network simulations on a network "similar" to the Berlin network and create artificial topologies with a topology generator. In many simulations, a simple uniform generator is used, i.o.w. the nodes are distributed uniformly on the terrain. For the case of the Berlin network a generator might produce an artificial topology such as the one shown in Figure 5, using the same number of nodes and area as the real-world Berlin network.

A. Nearest Neighbor Distance Distribution

Table I summarizes the network characteristics: as can be seen, the level of spatial clustering influences the average nearest neighbor (NNB) distance in relation to the average

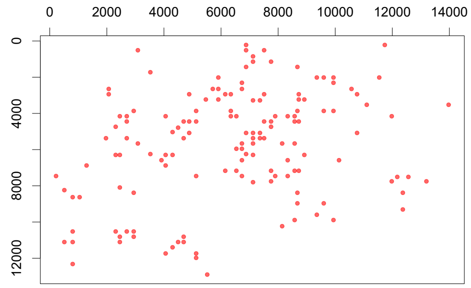

Fig. 3. Real-World Node Positions: Vienna (scale in meters).

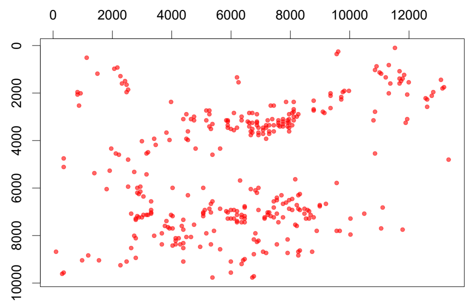

Fig. 4. Real-World Node Positions: Berlin (scale in meters).

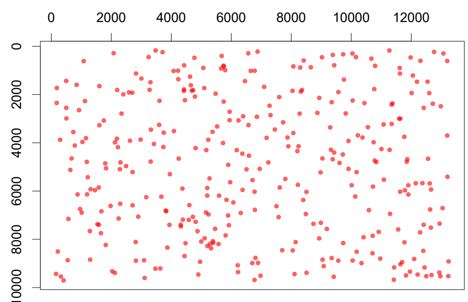

Fig. 5. Artificial topology using the same area and number of nodes as the Berlin network but with uniform distribution (scale in meters).

node distance. E.g., the Vienna and Berlin networks have quite similar average node distances, but due to the higher clustering the average NNB distances are much lower in the Berlin network. While investigating NNB distance w.r.t. communications range gives an indication of the probability that a network will be connected when using a certain radio technology, considering NNB distance alone is not enough. For a comparison of networks, NNB distance should always be considered in combination with the average node distance and density. E.g., the Leipzig and MIT Rooftop networks don't differ much in their average NNB distance but taking their size differences into account – the MIT Rooftop network covers an area only about 16% the size of the Leipzig network – it becomes apparent that the Leipzig network must be a lot more clustered. When evaluating the artificially created topology, we can see that in the real-world Berlin network the average

TABLE I
NETWORK PROPERTIES.

	MIT	Leipzig	Vienna	Berlin	Artificial
Number of nodes	81	425	145	339	339
Size [km^2]	7.01	43.37	186.23	132.55	132.55
Density [nodes/km^2]	11.56	9.799	0.779	2.558	2.558
avg. Node Dist. [m]	1022	2333	5424	4742	6036
avg. NNB Dist. [m]	104	78	438	198	336
avg. ND/avg. NNB	9.83	29.91	12.38	23.95	17.96
Inhomo. Factor h	0.58	0.656	0.448	0.454	0.115

NNB distance is a lot shorter, implying higher clustering. Such a mismatch should prompt the use of a different topology generator; e.g. [7].

B. Propagation Model Based Node Degrees

To calculate node degrees from a position-based topology, a propagation model has to be applied. With the propagation model, the distance matrix can be converted to a connection probability (CP) matrix. Without restriction of generality, we choose the following example:

- a Rayleigh fading model which is suitable for modelling radio propagation in urban environments. We calculate the expected reception power at the receiver as

$$E\left[P_r\right] = P_t g_t g_r \left(\frac{c}{4\pi f}\right)^2 \left(\frac{d}{d_0}\right)^{-\alpha}, \qquad (1)$$

  where P_t is the transmission power at the sender, g_t, g_r the antenna gains at sender and receiver respectively, d the distance between sending and receiving node, $d_0 = 1\,\mathrm{m}$ the reference distance, and α the path loss exponent [18],
- a path loss coefficient of $\alpha = 2.5$ (assuming that due to building codes that restrict building height in European cities there is mostly line-of-sight between rooftop-mounted mesh routers),
- commercially available wireless routers [19] with an assumed receiver threshold of $\theta = -97$dBm and sending power $P_t = 26$dBm, and
- high-gain antennas [20] with an antenna gain of $g_r = g_t = 5$dBi.

We can now calculate node degrees as described in Section II-B. Figures 6 and 7 show comparisons of the 95%-threshold degree and the probabilistic degree for our four networks and the "artificial Berlin" example topology from above. As can be seen, due to the longer NNB distances the artificial topology also exhibits much lower degrees for a given threshold than the clustered real-world topology.

C. Inhomogeneity Factor

We calculate the inhomogeneity factor h developed in [11] (as described in Section II-C above). The results are given in the last line of Table I. As can be seen, our example artificial topology again shows a much lower inhomogeneity factor – meaning its nodes are a lot more homogeneously distributed – than the real-world topology of Berlin. Therefore, this artificially created topology is not a good model for the Berlin network.

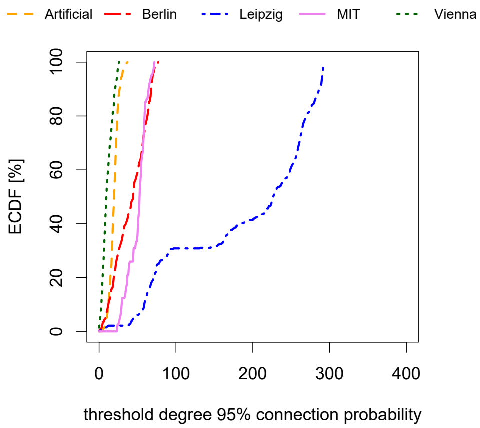

Fig. 6. Threshold Degree Comparison

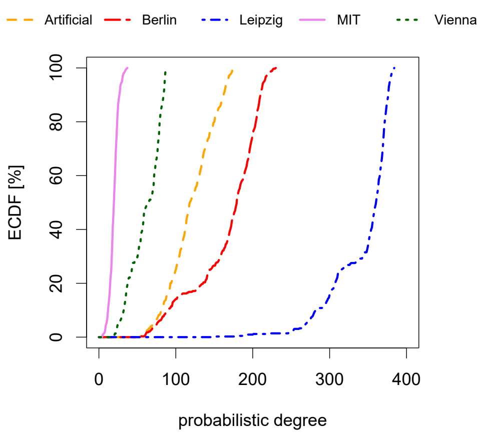

Fig. 7. Probabilistic Degree Comparison

IV. Conclusion

In wireless network simulation topologies are typically not defined as graphs but as the combination of spatial node positions and a propagation model. Therefore, it is important to be able to characterize such position-based topologies, esp. to judge the validity of artificially created models.

We proposed four metrics for this use case – nearest neighbor distribution, threshold degree, probabilistic degree, and inhomogeneity factor – and demonstrated their application using four real-world networks and an artificially created topology as examples.

Our examples show that real-world topologies are much more spatially clustered than a uniform distribution of nodes on the same terrain would be. The nearest neighbor metric and inhomogeneity factor can be used to directly assess the amount of clustering in such topologies while the threshold and probabilistic degree will give an indication of what to expect in terms of the resulting graph once the propagation model is applied. Consequently, we recommend to employ all four metrics in order to describe a topology with respect to its network properties and assess its validity for use in simulation.

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