Towards a Model for Global-Scale Backbone Networks

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***Abstract*—Synthetic network models play an integral role in nowadays research of computer networks. This is for the lack of real network data and to perform experiments with a statistical significant number of replications. While most of the modeling work currently focuses on layer 3 topologies, e.g., AS level, this work is on generating realistic layer 1 topologies. These topologies are of fundamental significance for network resilience, for example. By constructing β-skeleton graphs, augmented with population and technology indications, our approach is able to generate highly realistic graphs. This is shown by a comparison to US networks, whose topology is publicly available.**

***Keywords*—network model, physical layer topologies, beta skeleton.**

I. Introduction

Realistic Internet topology models are a key requisite for research in the networking area, allowing for experiments and prototypical simulative evaluation of novel protocols and distributed systems. While the vast majority of topology research focuses on generating network layer graph representations, physical characteristics are often neglected. This, however, may be particularly questionable as physical constraints of backbone networks strongly influence the properties of upper layer topologies. Apart from network layer connectivity, not only the most common network metrics, e.g., packet delay, are dominated by physical path properties, but also several more complex issues, e.g. network resilience and robustness.

Given the increasing number of (critical) network applications, these questions become even more interesting, hence there is demand for a generic but realistic model for physical layer topologies. Unfortunately, on the one hand, realistic models are typically only available for selected areas, i.e., where backplane topologies are approximated by known infrastructure lines [1]. On the other hand, existing synthetic models, i.e., involving random component placements, do not mirror characteristics of real networks at all.

For a planetary-scale physical topology model that represents characteristics of real backplane infrastructures we contribute the following approach: By instantiating node positions from real-world population densities that are biased by respective technology indicators and employing a beta skeleton graph structure that reflects real world constraints, we derive a realistic model for any country or region. Additionally, by augmenting the model with mapped submarine cable positions, we obtain an overall generic model for global-scale topologies that allows for an arbitrary number of instantiations. These different instantiations may then be used to generate a statistical significant number of repetitions in experiments.

In the course of the article, we pursue the following steps: We summarize objectives for a generic global-scale model and use them to categorize existing methods in Sec. II, we present a novel modeling technique for global-scale backbone topologies (Sec. III), and in Sec. IV we evaluate model characteristics by comparing synthetically generated instances to real-world networks. The article concludes in Sec. V.

II. System Objectives & Related Work

A generic global-scale backbone model should meet the following objectives:

Real-world Characteristics: Existing infrastructures are widely dominated by cost constraints, but also influenced by geographic and political conditions. The resulting characteristics of real-world backbone topologies should be reflected by synthetic graphs. Furthermore, basic structural properties, e.g., graph density or average path lengths, should be similar to real-world values.

Instantiation Diversity: Instances derived from a network model should exhibit diversity, i.e., allowing for statistically significant studies and experiments. Thus, (trace-driven) generator components that solely depend on measured traces and predetermined maps are to be avoided.

Simplicity: The heterogeneity of transport network properties around the globe should be reflected by the infrastructure model without relying on dedicated infrastructure maps. Furthermore, excessively complex modeling techniques involving unreasonable large parameter sets are to be avoided.

In the following, we provide a short overview on existing models for backbone topologies. Beyond the diversity of studies on (logical) network layer characteristics of the Internet maps, e.g., in the context of the Rocketfuel [2] and CAIDA [3] projects, the research interest on physical connectivity awakened during the recent years. Most notably, physical layer connectivity and its implications on higher layer connectivity is of serious interest, e.g., addressed by [4]. In addition, physical network knowledge must be considered crucial for an analysis of network resilience, i.e., particularly with regard to geographically correlated challenges (cf. [5], [6], [7]). Among others, studies in the context of the ResiliNets project [8] were concerned with resilience, paying particular attention to physical characteristics. Following up previous work, the authors of [9] formulate different graph models for the physical fiber topology of the United States, including a geometric graph model, a so-called geographic threshold graph model, a probabilistic Waxman model and the parameterless Gabriel graph model. On the one hand, during a comprehensive comparison of the given models, the Gabriel graph model was found to best capture the typical grid-like structure of physical backbone topologies. On the other hand, other models resemble star-like structures better and, when compared to a

real-world topology, even the grid-like structures appear considerably dense. However, given the set of compared models, Gabriel graphs were found to be the closest to reflect the US backbone topology. Nevertheless, like shown in Sec. IV, they still tend to create too dense structures.

III. Modeling Global-scale Backbone Networks

Given the heterogeneous nature of the earth surface, an overall model for physical backbone networks must consider a diversity of characteristics. The proposed model can be separated into three stages: node placement, landline connection modeling, and submarine line integration.

A. Population-based Node Placement

Both intuition and previous studies provide abundant evidence that the occurrence of PoPs (Point of Presence) strongly correlates with population characteristics. However, the sole dependency on population density is obviously misleading when considering the diversity of economical and technological standards around the world, e.g., despite the significant population, the amount of PoPs located in most central African countries is almost negligible when compared to European or North American states. Hence, we generate potential node placements as follows:

First, city-level population data is derived from *GeoNames* [10], a publicly accessible geographical database.

Second, the population values are additionally weighted by a country-dependent technology factor that is derived from the percentual number of Internet users per country (i.e., a relation that was already found reasonable in [11]). Respective statistics can be queried from the popular publicly accessible *UNdata* [12] database, being partially operated by the United Nations Statistics Division.

Third, we apply a density-based cluster technique, i.e., namely the OPTICS [13] algorithm, to group and aggregate nearby nodes. Similar to the well-known DBSCAN algorithm, OPTICS requires only two parameters: $MinPts$, which describes the number of points required to derive a cluster and the maximum radius ε taken into consideration. Returning to the node placement procedure, close by sites are grouped by parameterizing the algorithm with $MinPts_{close} = 2$ and a small valued maximum distance ε_{close} (see Fig. 1). In addition, we propose to also group metropolises, as they are often found separated into districts in the population datasets, by applying the algorithm with slightly higher thresholds $MinPts_{metro}$ and ε_{metro}. Finally, given the weighted population-values and a basic distribution function, a set of node locations can be sampled. For simplicity, we propose that all cities with a weighted population value of at least p_{min} become a potential PoP location, where a uniform distribution is applied for sample generation. Although leaving the scope of this article, more complex parameterization and distribution functions are applicable as well.

B. Landline Connections

Next, the selected set of PoPs must be connected in a way that the resulting graph structure reproduces basic characteristics of real-world networks. From a phyical layer

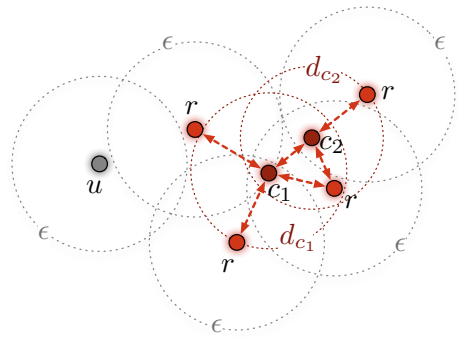


Fig. 1. Examplary OPTICS application for $minPts = 3$ and well-chosen parameter ϵ (i.e., not undefined)): Nodes c_1 and c_2 exhibit defined core distances d_{c_1} and d_{c_2} as $MinPts$ nodes are in their ϵ-neighborhood. Nodes denoted by r have defined reachability distances towards nearby nodes. Both core and reachability distances of node u remain unclassified, i.e., the respective ϵ-neighborhood is empty.

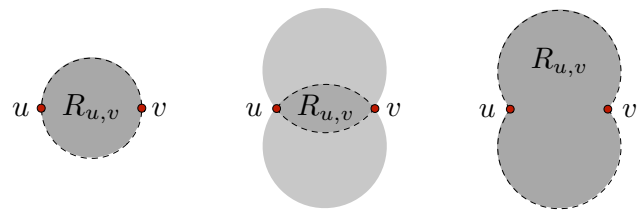
perspective, today's Internet is a network of mixed structure: While the edge of the backbone infrastructure appears to be dominated by locally restricted star- and tree-like structures, the core network is dominated by a mesh-like backbone (often referred to as ring-like backbone from a higher layer perspective). Basically, the following facts are pivotal to the shape of the geographical backbone graph: On the one hand, backbone providers not only aim for high connectivity, but also reasonable resilience in case of node and link failure. On the other hand, they naturally favor cost-optimizing connection sets, i.e., minimizing the overall length of deployed links. Subsequently, mesh-like structures arose, often showing a grid-like shape, providing high connectivity while inducing modest costs.

Hence, it is hardly surprising that the authors of [9] found a synthetic model based on Gabriel graphs highly promising: Gabriel graphs reflect cost-minimizing objectives of real-world structures and are known to perform well in resembling grid-like structures. However, Gabriel graphs are limited in representing heterogeneous link densities observable in real networks around the globe. Hence, we instead propose the use of the more generic β-skeleton graphs. Given a set of nodes V located on a Euclidean plane and a single parameter β, the β-skeleton defines an undirected graph $G = (V, E)$ where the edges E are derived as follows [14]:

$$\Theta = \begin{cases} \sin^{-1}(1/\beta), & \text{if } \beta \geq 1 \\ \pi - \sin^{-1}(\beta), & \text{if } \beta < 1 \end{cases} \qquad (1)$$
$$E = \left\{ \{u, v\} \in \binom{V}{2} \mid \nexists w \in V : \angle(uwv) > \Theta \right\}$$

Please note that the angle $\angle(uwv)$ refers to the angle between $\overline{wu}$ and $\overline{wv}$. The graph definition is illustrated in Fig. 2, where the node locations u and v define a geographic region $R_{u,v}$ that corresponds to either the intersection (Fig. 2b) or the union (Fig. 2c) of two circular shapes. An edge $\{u, v\}$ is contained in E if and only if there is no node position $w \in V$ that is located within $R_{u,v}$. Please also note that Gabriel graphs are an instance of β-skeletons, i.e., they are equal iff $\beta = 1$ (Fig. 2a).

Addressing a global-scale model, we found that β-skeleton graphs are to be favored over Gabriel graphs: Without sacri-



(a) β = 1.0 (Gabriel graph) (b) β = 0.8 (c) β = 1.25

Fig. 2. β-skeleton: Relevant areas $R_{u,v}$, i.e., dependent on parameterization.

ficing the general link to real-world characteristics, β-skeleton graphs allow for a generic adjustment of graph densities according to real-world characteristics. To give a real-world example, the backbone infrastructure in the Central European countries is considerably dense while the landline network on the African continent is extremely sparse. Basically, a reasonable correlation between the technological standard of a specific country and its respective physical network density can be assumed. Thus, we propose to adapt the parameter β within the limits β_{min} and β_{max} based on the respective percentual amount $T_{country}$ of Internet users (which is averaged if connection endpoints belong to different countries). For sake of simplicity, we assume direct proportionality between the according limits in order to determine $\beta_{country}$, i.e.:

$$\beta_{country} = T_{country} \cdot \beta_{min} + (1.0 - T_{country}) \cdot \beta_{max} \quad (2)$$

Please note, both β_{min} and β_{max} may have a major impact on the resulting graph connectivity and must be defined carefully. Nevertheless, independent network partitions are well-known to exist in landline connections, e.g., in Africa and central Asia. This feature cannot be described by pure Gabriel graphs.

Although leading to reasonable landline infrastructures for rather populated regions, the synthetic graph fails to reflect the influence of extremely underpopulated areas: Considering real networks, landline connections typically do not traverse large uninhabited zones, e.g., desserts or mountain massifs. Hence, an additional filter is applied to the beta skeleton graph structure in order to exclude long-range edges that traverse geographically extraordinary, underpopulated areas. A number of filter strategies may be considered reasonable, among we propose the following: Given the previously applied population-based node placement technique as well as the β-skeleton characteristics, we consider continental connections that exceed a maximum length d_{max} to be entirely unrealistic as they implicitly traverse seriously underpopulated areas. However, d_{max} should not be assumed to be globally unitary, e.g., due to different economic preconditions and connectivity demands, North American landline connections may connect more distant nodes than African landline connections. Hence, we additionally adapt the maximum length threshold d_{max} by the previously involved country-dependent technology factor $T_{country}$ in order to derive $d_{max,country}$:

$$d_{max,country} = d_{max}(1.0 + T_{country}) \quad (3)$$

As before, $T_{country}$ is averaged if line endpoints belong to different countries. Finally, each edge exceeding the according maximum length is removed from the graph structure.

Node placement	$p_{min} = 75 \cdot 10^3$	
Cluster (closeby)	$MinPts_{close} = 2$	$\varepsilon_{close} = 30km$
Cluster (metro)	$MinPts_{metro} = 4$	$\varepsilon_{metro} = 50km$
Landline links	$\beta_{min} = 1.0$	$\beta_{max} = 1.2$
Length filter	$d_{max} = 600.0km$	

TABLE I. USED PARAMETER SET

As an alternative, the population values for a specific area around a long-range-edge, e.g., defined by a β-skeleton shape, could be scanned. Given additional weights that reflect population values, scanned point distance towards the edge and technology factors, edges may be filtered more fine-grained. However, in particular due to the limited evaluability of the results, the associated parameter set is difficult to manage and not considered reasonable. Therefore, we rely on the more simple method in the following.

C. Submarine Lines

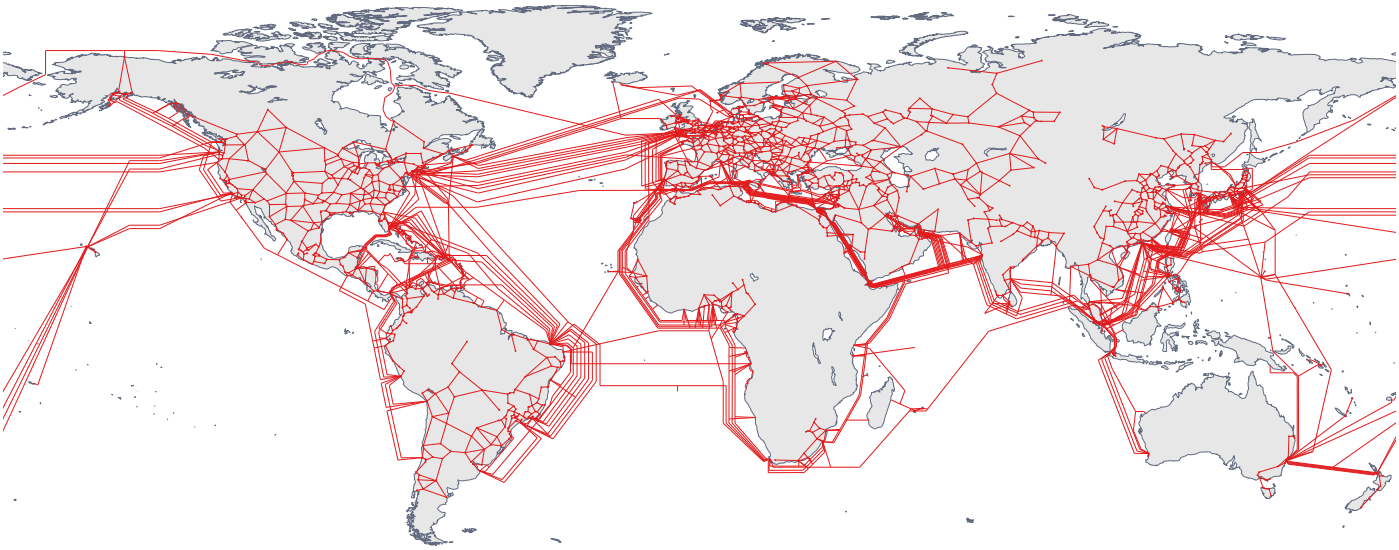
While landline connections can be synthetically approximated according to replicable economical, political and technological constraints, submarine lines must be treated separately due to their sole dependency on geographic characteristics. In contrast to the diverse landline links, undersea cables are comparably well documented for nautical reasons. They can be directly obtained from a freely accessible database, i.e., the Submarine Cable Map provided by TeleGeography [15].

IV. EVALUATION

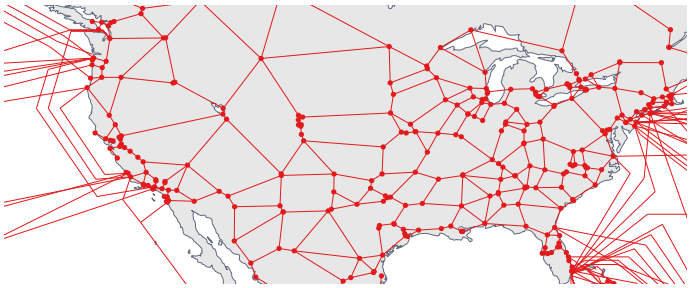
To assess the proposed model, we discuss the fulfillment of objectives that were formulated in Sec. II. This includes a visual review of the resulting graph infrastructure. In order to study the suitability of the obtained continental topologies more thoroughly, we compare synthetic graphs to real-world backbones by referring to publicly available US topology data. The evaluation was performed with the parameters given in Table I.

Real-world Characteristics: Already at first glance, the exemplary graph instance in Fig. 3a illustrates well-known characteristics of the real-world infrastructure. On the one hand, strongly populated and technologically advanced regions, e.g., Europe, Japan and North America, exhibit densely meshed backbone networks. On the other hand, the backbone graph appears considerably sparse in economically and technologically weaker regions, e.g., in South American and much of the Asian continent. Likewise, similar to real-world networks, landline connections are mostly absent in the structurally weakest and undeveloped areas, e.g., on the African continent. Instead, the populated coastline areas of the African continent are almost solely connected by submarine lines.

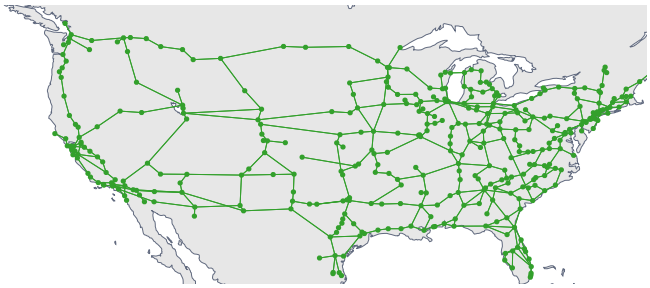
Unfortunately, reliable spatial information on real-world backbones is rarely available, in particular for sparsely populated areas. Due to the lack of reference data, a quantitative analysis of graph properties derived from the global model cannot be considered meaningful. An analysis of graph properties is only practicable for topological areas that are also represented by reference data. To the best of our knowledge, amongst considerably large areas, only the United States backbone network seems reasonably covered by publicly available data. Such data can be extracted from [16], where we focus



(a) World map (Synthetically generated instance)



(b) North America (Synthetically generated instance)



(c) North America (AT&T real-world L1 network)

Fig. 3. Synthetically generated backbone topology on global scale

Graph Metric	Sprint	Level-3	AT&T	Gabriel (AT&T L1 Locations)	Synthetic (AT&T L1 Locations)	Synthetic (Random)
Nodes	264	99	383	367	356	254
Edges	313	132	488	640	490	346
Node Degree	2.37 ± 0.052	2.67 ± 0.093	2.55 ± 0.059	3.49 ± 0.058	2.75 ± 0.046	2.72 ± 0.055
Closeness	0.07 ± 0.001	0.14 ± 0.002	0.07 ± 0.001	0.09 ± 0.001	0.07 ± 0.002	0.08 ± 0.001
Betweenness	0.05 ± 0.004	0.06 ± 0.007	0.03 ± 0.059	0.03 ± 0.002	0.04 ± 0.001	0.05 ± 0.004
Diameter	37	19	39	34	37	37

TABLE II. SELECTED PROPERTIES OF REAL-WORLD AND SYNTHETIC TOPOLOGIES.

on the recorded physical networks of *Sprint*, *Level-3*, and *AT&T* (see Fig. 3c), being the most prominent US Tier-1 providers. The first columns in Table II provide an overview on graph properties of the mentioned provider topologies. Node degree, closeness, and betweenness are given by their average values and standard deviation. A more detailed analysis of the structural properties can be found in [17]. Hardly surprising, all backbone topologies exhibit an average node degree between 2 and 3. Unlike the strongly meshed logical topologies observable on upper layers, small node degrees are distinctive for physical networks of single providers. The right-hand side columns of Table II refer to synthetically generated networks, which of the two leading columns involve fixed node positions taken from the AT&T graph, being the largest provider network. The first of the columns shows the properties of the best previously known algorithm based on Gabriel graphs [9], which differs significantly from the real-world topology especially in node degree. Our synthetic landline placement technique applied on the very same node positions shows more similar properties. Moreover, the very last column shows properties for a synthetic graph with random node positions bound to the US (see Fig. 3b), indicating a similarity of topological characteristics as well.

When comparing graph properties, a significant problem remains: There are many degree-2 nodes contained in the real-world graphs only to describe the geographic shape of lines. This issue was found already in [9], where the authors modified the topologies by removing all degree-2 nodes. However, this has serious impact on the graph characteristics and hardly be considered adequate for a comparative evaluation.

Hence, instead of solely assessing graph-theoretic metrics, we focus on the discussion of end-to-end characteristics. For this purpose, first, a fixed amount of random locations within

a US bounding box is chosen. Second, the closest topology element in terms of spherical distance is determined for each location and the chosen location is connected to the topology either via perpendicular segment if the closest element is a link or a direct edge in case of a node. Third, the shortest distances between all pairs of the chosen locations are calculated.

To start with, we examine the proposed algorithm for landline connection placement more detailed, thus drawing on the physical node positions of the AT&T graph. Previous work found Gabriel graphs to be suited for representing the US backbone topology, i.e., when compared to other prominent modeling techniques. Thus, we first compare the end-to-end distances, i.e., the shortest path on the physical graph, between the randomly chosen locations for both the AT&T topology and the Gabriel graph with AT&T node positions. Fig. 4 illustrates

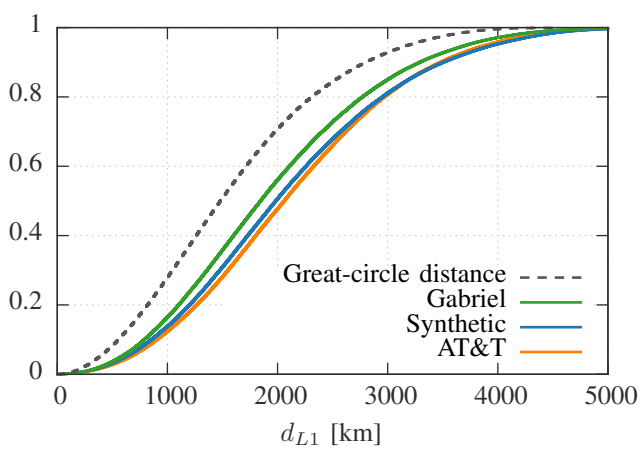


Fig. 4. Length of random paths on top of the AT&T physical network compared to the respective lengths on top of a synthetically generated instance.

the resulting cumulative distribution functions of end-to-end distances. The great-circle distance (i.e., the shortest distance on the sphere surface) between these locations is depicted for comparison. For now, particular attention should be drawn to the significant gap between the distance distributions of the AT&T graph and the Gabriel graph. Fig. 5 illustrates the according Q-Q plot, where the quantiles of the respective sets of determined end-to-end distances are plotted against each other. Most notably, the left-aligned offset between the plotted percentiles when compared to $f(x) = x$ indicates that the generated Gabriel graph is more densely connected than the real-world counterpart. This is also indicated in Table II by both a comparatively high amount of edges generated by the Gabriel graph and, as a result, the considerably higher node degree. In the same way, the end-to-end distance distributions for both the AT&T topology and a synthetic instance with AT&T node positions that is generated according to our method are compared. The resulting cumulative distribution function (see Fig. 4) already suggests close proximity to the real-world AT&T topology. The according Q-Q plot is depicted in Fig. 6, revealing comparably broad similarity, thus indicating a notable topological replication achieved by the β-skeleton-based algorithm.

Up to now, we referred to the physical node locations of the AT&T graph. However, in order to be able to examine the overall synthetic model in terms of resulting characteristic

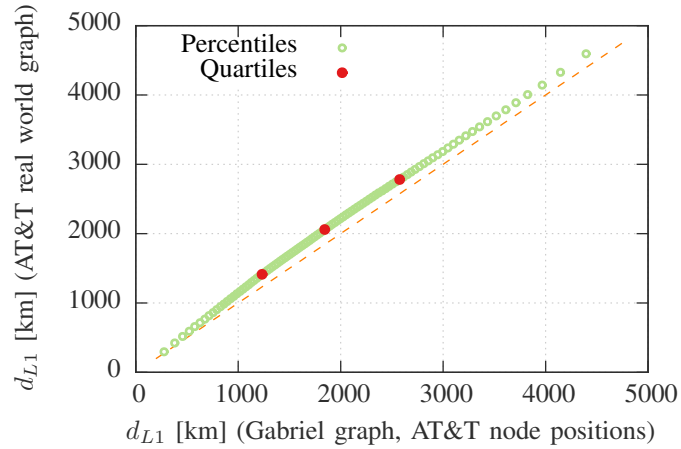


Fig. 5. Quantile-Quantile plot comparing the distance distribution of AT&T physical network and Gabriel graph topology with AT&T node placements.

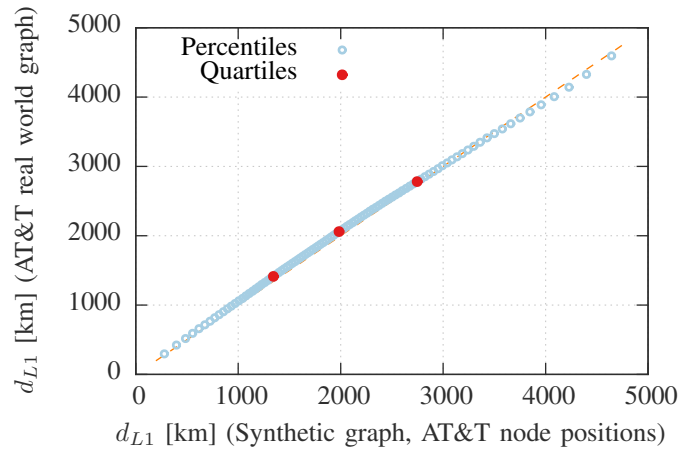


Fig. 6. Quantile-Quantile plot comparing the distance distribution of AT&T physical network and β-skeleton-based graph with AT&T node placements.

similarity with the real-world topology, we now apply our random node placement technique. The resulting Q-Q plot is illustrated in Fig. 7, again indicating broad similarity, i.e., due to the associated points approximately lying on $f(x) = x$. Most notably, the distance distribution is not considerably affected by the varied node placement, resulting in a synthetic topology that still reflects real-world end-to-end characteristics.

Instantiation Diversity: With the exception of submarine cable embedding, the proposed method does not rely on traced component positions nor on predetermined infrastructure samples. In order to give an impression on the diversity of synthetically generated topologies we compared the topological distances between the two nodes that have the highest-degree of landline connections for a set of instances. Fig. 8 illustrates the distribution of distances between these node pairs. The left-hand side histogram shows topological distances on global scale, indicating that the major amount of these distances is considerably short, as the highest degree nodes are most often found on the same continent, i.e., Europe, due the dense population. Accordingly, the significant peak for distances between 10000 km and 15000 km is attributed to distances where the nodes in question are located on different continents.

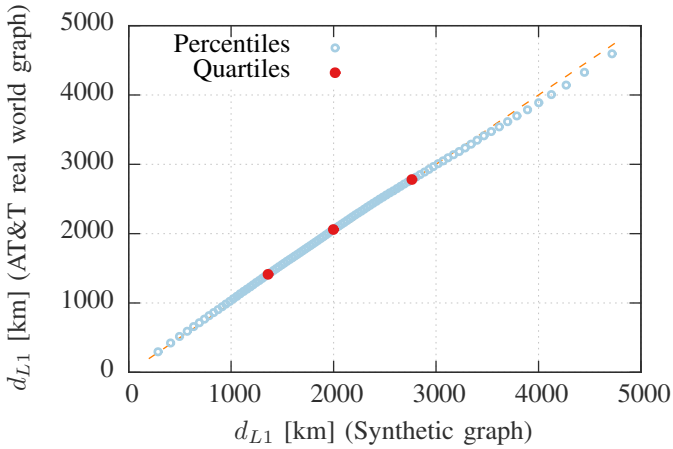


Fig. 7. Quantile-Quantile plot comparing the distance distribution of AT&T physical network and synthetically generated instance.

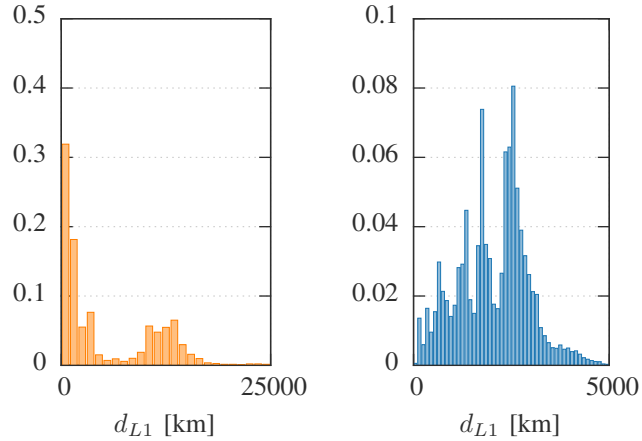


Fig. 8. Distribution of distance d_{L1} between nodes with highest degree (excluding submarine connections) for a set of generated instances. The distance between highest degree nodes on global scale is considered on the left hand figure while the right hand figure illustrates distances between highest degree nodes in the US.

The right-hand side histogram analogously depicts the distance distribution in the US bounding box. According topological distances are skewed where peaks follow characteristic distances between highly populated areas, e.g., the peak at around 3500 km addresses distances between metropolitan areas on the West and the East Coast.

Simplicity: The proposed technique does not rely on complex modeling techniques nor extraordinary large parameter sets. Both the number of topological nodes and the topological density of edges can be modified easily, i.e., by adapting the population threshold value and the metropolitan cluster setup as well as the β-skeleton parameterization. Currently, this does not yet apply to the submarine cables, which cannot easily be generated from scratch without sacrificing representativity due to their anomalous real-world placement.

V. Conclusion

Physical network models play an integral role for computer network research. This paper contributes an evolved approach for both: node positioning and landline placement. The evaluation showed that this approach is well suited to model networks for large geographic regions. The toolset is available at tu-ilmenau.de/telematik/topogen and may also augment submarine cables to generate global models.

Future enhancements of the system will consider effects of different regulatory zones, i.e., physical networks grow differently within and between countries. Furthermore, a network layer model needs to be mapped on the generated physical backbone topologies, e.g., to derive AS information. Another possible extension would model submarine lines to artificially generate a statistically significant number of submarine cable graphs.

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