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Topological analysis of urban street networks

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Abstract. The authors propose a topological analysis of large urban street networks based on a computational and functional graph representation. This representation gives a functional view in which vertices represent named streets and edges represent street intersections. A range of graph measures, including street connectivity, average path length, and clustering coefficient, are computed for structural analysis. In order to characterise different clustering degrees of streets in a street network they generalise the clustering coefficient to a *k*-clustering coefficient that takes into account *k* neighbours. Based on validations applied to three cities, the authors show that large urban street networks form small-world networks but exhibit no scale-free property.

1 Introduction

Network analysis has long been a basic function of geographic information systems (GIS) for a variety of applications in, for example, hydrology, facilities management, transportation engineering, and business and service planning. In network GIS, computational modelling of an urban network (for example, street network or underground) is based on a graph view in which the intersections of linear features are regarded as nodes, and connections between pairs of nodes are represented as edges. Common network operations include computational processes to find the shortest, least-cost, or most-efficient path (*pathfinding*), to analyse network connectivity (*tracing*), and to assign portions of a network to a location based on some given criteria (*allocation*) (Miller and Shaw, 2001; Waters, 1999).

A network GIS can be also analysed with respect to its structural properties: for example, which are the important streets of a city in terms of connectivity? What is the average level of integration or segregation of a street network? Overall, how are those streets interlinked? All these questions deal with topological, logical, and structural properties that are the scope of urban morphology. For instance, space syntax (Hillier and Hanson, 1984) adopts a graph-theoretic method to model how urban spaces are integrated or segregated using so-called 'axial maps'. The derivation of axial maps relies to a great extent on the structural properties of a given street network and the allocation of buildings within such an urban environment.

In this paper we take a 'named-streets'-oriented view for topological analysis. 'Named streets' represents a functional modelling element of large urban street networks whose structure should be retained by a structural analysis. Evaluating the degree to which streets are interconnected versus segregated in a given city should imply, at a modelling level, designing a graph in which the nodes model those named streets and edges model connections between those named streets (note that in such a view a node models not a street segment but an entire named street). Without loss of generality, a named street that is separated into two or more parts (for example, South Queen

Street and North Queen Street) is semantically aggregated. One of our objectives in this paper is to explore such an alternative graph model. This named-street-centred network model is denoted as a topological network model, as it reflects at a higher level of abstraction topological connections in a given street network (and not purely geometrical connections).

The topological network model supports a street-oriented computational analysis of the properties of an urban street network. We develop a computation based on a range of graph-based measures completed by a k-clustering coefficient which extends the current definition of the clustering coefficient to the integration of k neighbours. The aim of our model and study is to examine whether or not a named-street-oriented topology reveals small-world and scale-free properties for urban networks. A small-world network is a large network with a short average separation between any two randomly chosen nodes, and highly clustered nodes, compared with a random network of equivalent size (Watts and Strogatz, 1998). A scale-free property over a function $y = \mathrm{f}(x)$ reveals the fact that whatever the range of x one looks at, the proportion of small to large y values is the same, that is, the slope of the line on any section of the log–log plot is the same. A scale-free network denotes a network where most nodes have a small number of links, and only a rare few have a large number of links (Barabasi and Albert, 1999).

Small-world and scale-free properties have been investigated and illustrated in a variety of disciplines and domains, including biology (Jeong et al, 2000), ecology (Montoya and Sole, 2002), linguistics (Cancho and Sole, 2001), and computing on the Internet (Faloutsos et al, 1999; Shiode and Batty, 2000). In particular, this approach has been used in social science to analyse the structure of so-called social networks (Scott, 1999). For a comprehensive overview on small-world and scale-free properties, see, for instance, Strogatz (2001) and Barabasi (2002).

The remainder of this paper is organized as follows. In section 2 we briefly discuss how small-world and scale-free properties apply to regular, random, and real-world networks. In section 3 we consider an example of an urban district for topological measures for individual streets. In section 4 we introduce the concept of the k-clustering coefficient to characterise the clustering degrees of streets in large networks. In section 5 we report our experimental results and in section 6 draw some conclusions.

2 Regular, random, and real-world networks: small-world and scale-free properties

A network can be represented as a graph which consists of a finite set of vertices (or nodes) V and a finite set of edges (or links) E (note that we use the terms 'vertices' and 'nodes', and 'edges' and 'links' interchangeably). A graph is often denoted as a pair $G(V, E)$, where V is the set of vertices, $v = \{v_1, v_2, \dots, v_n\}$, and E the set of edges, is a subset of the Cartesian product $V \times V$. For computational purposes we represent a connected, undirected, and unweighted (that is, all links with a unit distance) graph by an adjacency matrix $\mathbf{R}(G)$:

$$\mathbf{R}(G) = [r_{ij}]_{n \times n} ,$$

where

$$r_{ij} = \begin{cases} 1, & \text{if } v_i v_j \in E, \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

It should be noted that for this adjacency matrix $\mathbf{R}(G)$ is symmetric, that is, $\forall r_{ij} \Rightarrow r_{ij} = r_{ji}$, and that all diagonal elements of $\mathbf{R}(G)$ are equal to zero. Then the lower or upper triangular matrix of $\mathbf{R}(G)$ is sufficient for a complete description of the graph G. In the context of this research, we deal with large networks with hundreds or thousands of nodes. A regular network is defined as a graph where each node has exactly the same number of links to its neighbouring nodes. Examples of regular networks are a regular grid where all nodes have exactly four links, and a hexagonal lattice where each node is connected to three other nodes (Gross and Yellen, 1999). Such regularity is clearly absent in random networks, as links are randomly placed among the nodes. Despite the fact that links do not show a regular pattern in large networks, it has been observed that the distribution of connectivity in random graphs follows a bell-shaped curve where most nodes have the same number of links, and there are no highly connected nodes (Barabasi, 2002).

Networks observed in reality or underlying real-world systems are so-called 'real-world networks'. They include, for instance, the Internet, scientific collaboration networks, cells, and scientific citations. Real-world networks are likely to be small-world networks that demonstrate two basic properties (Watts and Strogatz, 1998). The first property is that the separation between any two randomly chosen nodes is very short. The separation is characterised by the notion of a 'path', which is defined as the shortest distance between nodes. The average path length for a social network is likely to reflect a short degree of separation. According to Milgram (1967), an empirical study was carried out to testify the concept of six degrees of separation in the United States. He first randomly chose two target persons in Boston. Then he sent 160 letters to randomly chosen residents of two areas, one in Kansas and one in Nebraska, which are far away from the target persons. Surprisingly the first letter arrived, passing through only two intermediate links! Eventually he found that the median number of intermediate persons involved in getting the letter to the target was 5.5—very small indeed. Although the property of short separation in social networks is generally accepted, we can note that recent studies have mirrored Milgram's findings (Kleinfeld, 2002; Watts, 2003). In particular, further experiments question the value of six degrees of separation in a worldwide setting (http://smallworld.sociology.columbia.edu/index.html). In the domain of the Internet, Albert et al (1999) found that the web forms a kind of small-world network with a separation from page to page of around nineteen clicks. Mathematically, such a separation can be described by average path length. Given two vertices $v_i, v_j \in V$, let $d_{\min}(i,j)$ be the shortest distance between these two vertices. The *average path length* of a given vertex v_i is given by

$$L(v_i) = \frac{1}{n}\sum_{j=1}^{n} d_{\min}(i,j), \tag{2}$$

where n is the total number of vertices of the graph G. It should be noted that the average path length is a topological measure, which is of interest in the structural analysis of large networks.

The second property of small-world networks is their high degree of clustering. This can also be seen from our daily experience where, for example, our friends are likely to be friends of each other as well; in other words, social networks tend to be clustered. As to how high the possibility is, this depends on actual friendship links among our friends. Let us assume that one has four friends. If they are all friends with each other, then there will be six friendship links. However, the actual links counted are fewer than 6 links—let us say, 4. In this case, the likelihood of any pair of individuals being friends of the four people is $4/6 = 0.667$. Watts and Strogatz (1998) introduced a clustering coefficient to characterise the degree of clustering. Mathematically, the *clustering coefficient* is a measure of the extent to which the neighbours of a vertex v_i are also linked to each other. The clustering coefficient of the vertex v_i is defined by

$$C(v_i) = \frac{2l_i}{m_i(m_i - 1)}, \tag{3}$$

where l_i is the number of edges among the immediate neighbours of the vertex v_i, and m_i the number of immediate neighbours of the vertex v_i. We can note that $C(v_i)$ is drawn from the unit interval $[0, 1]$. The closer to unity the clustering coefficient is, the more clustered the vertex v_i is.

A high degree of clustering is an important property of regular graphs, as long as the neighbouring nodes for every node are well linked, as shown in figure 1. However, regular graphs are not likely to reveal small-world properties, as the shortest path length that connects two given nodes is likely to have a large degree of separation for large graphs.

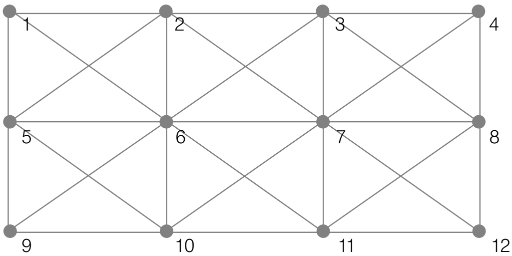


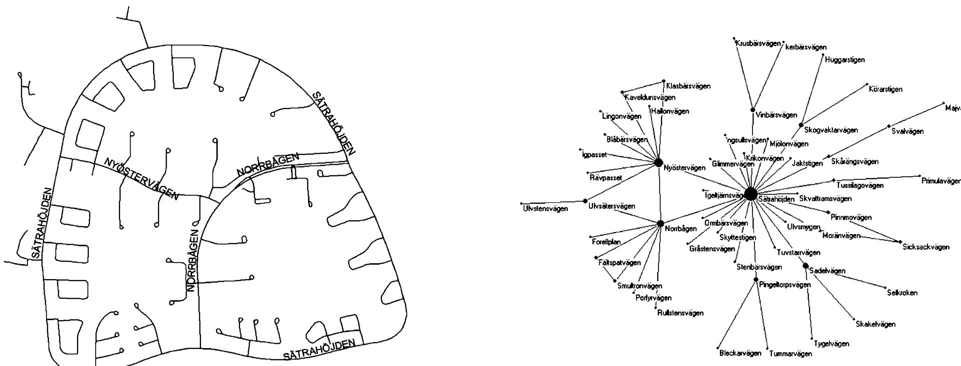
Figure 1. Illustration of a highly clustered regular graph (the average clustering coefficient for all nodes is equal to 0.705).

Besides the small-world property, the scale-free property is another important feature of most real-world networks. This is related to the notion of connectivity denoted by m, that is, the number of links (or immediate neighbours) of a node. The scale-free property reflects the fact that in a given network most of the nodes have a small connectivity and only a few nodes have a very high connectivity. Overall, distribution of connectivity in most real-world networks follows a power-law distribution (Barabasi, 2002). Power laws, initially introduced by Zipf (1949) in linguistics, have a typical form of $\mathrm{f}(x) = cx^{\alpha}$, where c is a constant and α some parameter of the distribution. This differentiates a real-world network from a random network, as the distribution of connectivity of a random network essentially conforms to a bell-shaped exponential distribution, rather than power law (Barabasi and Albert, 1999). Many real-world networks, such as the Internet (Faloutsos et al, 1999), World Wide Web (Albert et al, 1999), scientific collaboration networks (Newman, 2001), cells (Jeong et al, 2000), and scientific citations (Bilke and Peterson, 2001) reveal a power-law distribution.

In a study of the formation of scale-free networks, Barabasi and Albert (1999) found that most real-world networks are governed by two laws: growth and preferential attachment. During the growth of a real-world network, early nodes are likely to have more links because of evolution. If one simulates such a network growth, it does not lead to highly connected nodes: instead, a random network with a bell-shaped connectivity distribution is created. Through careful observation of web growth, Barabasi and his colleagues find that, given all possible news pages, we tend to link to those major news outlets such as cnn.com or bbc.co.uk. This implies that page links have potential preference in linking to other pages. In other words, preferences are given to the nodes, which are already highly connected. The two laws appear to be applicable to the evolution of urban street networks as well. That is, early built streets tend to be connected by more other streets on the one hand, and preferences are given to the streets that are already highly connected on the other. In section 5.1, we examine whether or not this scale-free property exists in urban street networks.

3 Topology of urban street networks—a first look

Let us consider the example of a district of the Swedish city Gävle, as shown in figure 2. To the left of the figure is the street network of the district, Sätra; to the right is the corresponding connectivity graph. The derivation of the connectivity graph is based on the following transformation rule: named streets and their intersections give the nodes and links, respectively, of the connectivity graph. One can see that this district is a relatively closed one: a bell-shaped street Sätrahöjden constitutes a form of boundary, and it is internally connected by two streets (Norrbägen, Nyöstervägen) that form an internal communication link. These three main streets form the main structure of this district to which other short streets are connected.



(a) (b)

Figure 2. Sätra district network (a) and its connectivity graph (b). (Note: every node is labelled by the corresponding street name.)

For illustration purposes, table 1 lists three calculated measures for the first twenty streets (in reverse order of connectivity) of the fifty-one named streets of the Sätra district shown in figure 2. Although this example cannot be considered a large urban street network, some facts can be derived from table 1. One can see that most of the streets have a small connectivity, between 1 and 4, and only three of them have a very high connectivity (column m). This is also reflected in figure 2 where node sizes show the degree of connectivity. We can see that well-connected streets have shorter path lengths (column L), whereas less-connected streets have longer path lengths. As far as the clustering coefficient is concerned, one can see that most of the streets in column C have a coefficient of 0. This indicates that either (1) street networks are not highly clustered (this will be discussed in section 5) or (2) the coefficient measure introduced

Table 1. Three measures for the streets of parts of the Sätra district; connectivity (m), path length (L), and clustering coefficient (C).

Street	m	L	C	Street	m	L	C
Sätrahöjden	23	1.58	0.00	Klasbärsvägen	2	3.04	1.00
Nyöstervägen	10	2.08	0.07	Moränvägen	2	2.52	0.00
Norrbågen	8	2.12	0.11	Pinnmovägen	2	2.52	0.00
Sadelvägen	4	2.44	0.00	Sicksackvägen	2	3.46	0.00
Pingeltorpsvägen	3	2.48	0.00	Skårängsvägen	2	2.48	0.00
Skogvaktarvägen	3	2.48	0.00	Smultronvägen	2	3.08	1.00
Ulvsätersvägen	3	2.90	0.33	Svalvägen	2	3.42	0.00
Vinbärsvägen	3	2.48	0.00	Tussilagovägen	2	2.52	0.00
Fältspatvägen	2	3.08	1.00	Bleckarvägen	1	3.46	0.00
Kaveldunsvägen	2	3.04	1.00	Blåbärsvägen	1	3.06	0.00

by Watts and Strogatz (1998) does not differentiate various degrees of clustering among the streets of a network very well. This leads us to propose a generalisation of the clustering coefficient.

4 *k*-clustering coefficient

The clustering coefficient, hereafter denoted as 1-clustering coefficient, considers only immediate neighbouring nodes. However, a node with a low 1-clustering coefficient can be relatively highly clustered among its k neighbours. In order to characterise the situation better we introduce a measure, the k-clustering coefficient, that takes into account the degree to which the k neighbours of a given node are interconnected with each other or not. Let $l_i^{(k)}$ be the number of edges among k neighbours of vertex v_i and $m_i^{(k)}$ be the number of nodes within k neighbourhood of vertex v_i. The k-clustering coefficient, denoted $C_i^{(k)}(v_i)$, of a given node v_i is defined as follows:

$$C^{(k)}(v_i) = \frac{2l_i^{(k)}}{m_i^{(k)}(m_i^{(k)} - 1)} . \tag{4}$$

One can see that, with the above definition, the 1-clustering coefficient is a specialisation of the k-clustering coefficient measure for immediate neighbours, that is, $C(v_i) = C^{(k)}(v_i)$ when $k = 1$. As for the 1-clustering coefficient, the k-clustering coefficient is also bounded by the unit interval $[0, 1]$.

From its definition, the 2-clustering coefficient describes the degree to which those streets within 2-neighbourhood are interconnected with each other. If all those streets are interconnected with each other, then the 2-clustering coefficient is equal to 1; if none of those streets are interconnected, then the 2-clustering coefficient is equal to 0 (as for the 1-clustering coefficient). Table 2 shows that the 2-clustering coefficient has more variations among the individual streets. For instance, Sicksackvägen's 1-clustering coefficient is equal to 0 as its immediate neighbours have no link at all, whereas its 2-clustering coefficient is equal to 0.67 as there are two links among its three 2-neighbours.

Table 2. 1-clustering ($C^{(1)}$) and 2-clustering ($C^{(2)}$) coefficients for the streets of part of Sätra district.

Street	$C^{(1)}$	$C^{(2)}$	Street	$C^{(1)}$	$C^{(2)}$
Sätrahöjden	0.00	0.03	Klasbärsvägen	1.00	0.24
Nyöstervägen	0.07	0.05	Moränvägen	0.00	0.09
Norrbågen	0.11	0.05	Pinnmovägen	0.00	0.09
Sadelvägen	0.00	0.07	Sicksackvägen	0.00	0.67
Pingeltorpsvägen	0.00	0.08	Skårängsvägen	0.00	0.08
Skogvaktarvägen	0.00	0.08	Smultronvägen	1.00	0.32
Ulvsätersvägen	0.33	0.14	Svalvägen	0.00	0.33
Vinbärsvägen	0.00	0.08	Tussilagovägen	0.00	0.08
Fältspatvägen	1.00	0.32	Bleckarvägen	0.00	0.67
Kaveldunsvägen	1.00	0.24	Blåbärsvägen	0.00	0.27

5 Topology of urban street networks—experiments

In order to investigate the topology of urban street networks, further experiments were applied to three cities: Gävle (Sweden), Munich (Germany), and San Francisco (USA). Only part of San Francisco network was used for the experiments because of some constraints on dataset availability. The network datasets are composed of street central lines which are topologically interconnected, that is, no isolated streets exist. A computational script determines how each given street intersects with every other, and

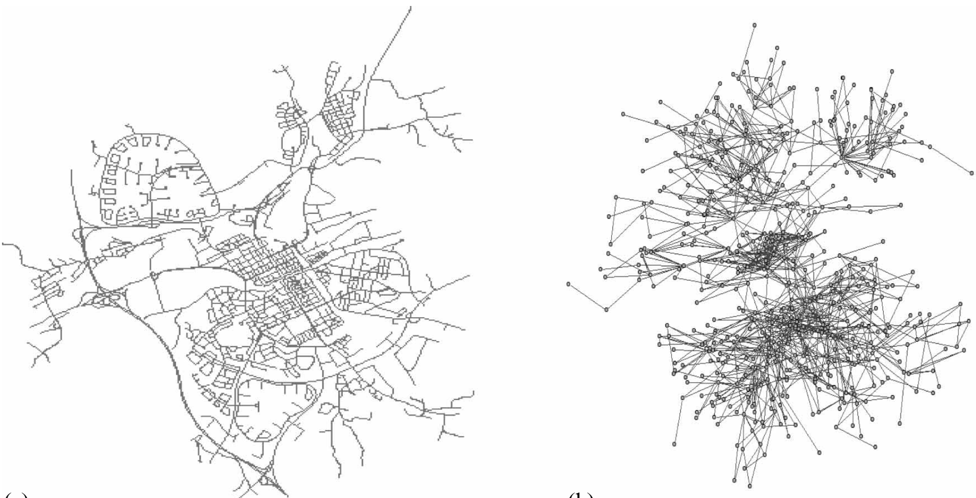


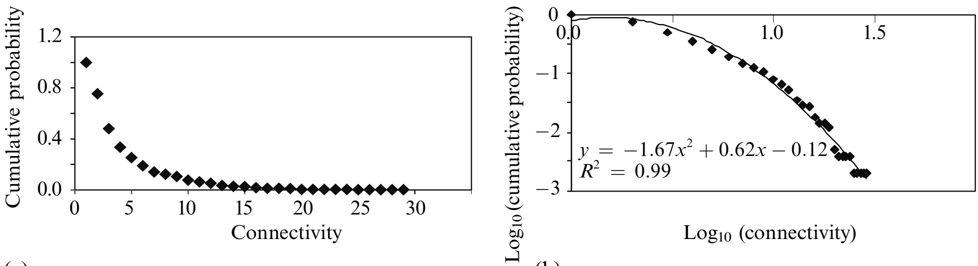
Figure 3. Gävle street network (a) and its connectivity graph (b).

derives a matrix **R** to represent the connectivity graph [see, for example, the Gävle case in figure 3(b)]. Informally the algorithm, with reference to equation (1), can be read as follows: for each street i, check if it intersects every other street j, if yes, $r_{ij} = 1$, otherwise $r_{ij} = 0$.

Using this algorithm, a street network can be mapped towards a matrix. The computational complexity of the algorithm is $O(n^2)$, so it is a relative costly process. The key to calculating the path length is to calculate the shortest distance between any two vertices by means of the Dijkstra (1959) algorithm. It should be noted that this shortest distance is not based on the geometry but, rather, on the topology. We first calculate the shortest distance from every vertex to every other and then sum all of them together to get a so-called 'total path length'. The algorithm begins at the first vertex and finds its neighbours, and then their neighbours, and so on until the algorithm has spanned throughout the graph and reached all vertices within a connectivity graph. This process is then continued with the second and third vertex until all vertices have been exhausted. In order to implement this algorithm, we adapted the breadth-first search (BFS) technique, which is considered to be a quite efficient method for finding the distance from one vertex to all the other vertices in a graph, and an extremely effective method for sparse graphs (Buckley and Harary, 1990). The average path length is the total path length divided by the total number of vertices n, and it is calculable in $O(n^2 \ln n)$ time. The computation of connectivity and 1-clustering coefficient is performed according to the formula introduced in section 2. They are calculable in $O(nm)$ and $O(nm^2)$ time, respectively. The k-clustering coefficient applies to the adjacency matrix of the subgraph corresponding to each vertex neighborhood; hence, it is calculable in $O(n^3)$ time.

5.1 Distribution of street connectivity

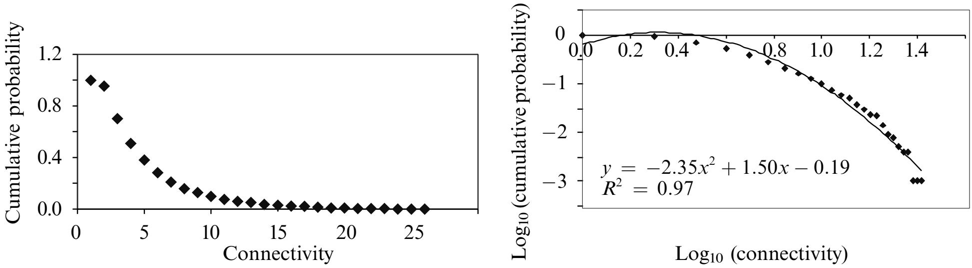
The first part of this analysis concerns the study of the scale-free property. Figure 4(a) (see over) shows a linear scale plot (of the Gävle case), where the x and y axes represent street connectivity and cumulative probability, respectively. One can see that most streets have a small connectivity (about 75% of the total 565 streets have connectivity ranging from 1 to 5), whereas a few streets have a large connectivity (25% of the streets have connectivity ranging from 6 to 29; in particular one street with connectivity of 29). Let y be the cumulative probability of occurrences per



(a) (b)

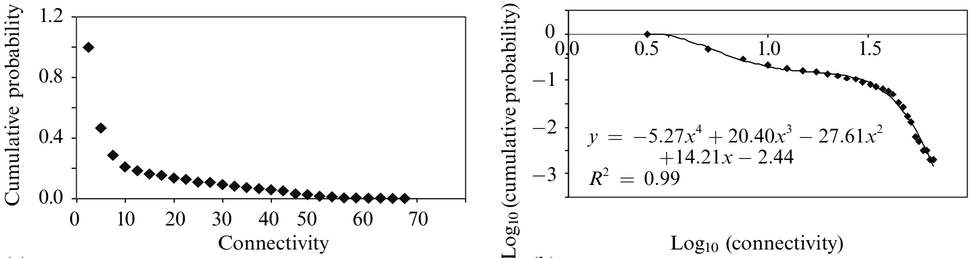
Figure 4. Gävle—Linear scale plot connectivity versus cumulative probability (a) and log–log scale plot connectivity versus cumulative probability (b).

cumulated connectivity rank x. If the cumulative probability y and x conforms to a power-law distribution for connectivity, we have $y = cx^{-a}$. This means that $\ln y = \ln c - a \ln x$; thus a power law with exponent a is seen as a straight line with slope $-a$ on a log–log plot. The log–log scale plot of street connectivity versus cumulative probability for the case of Gävle is shown in figure 4(b); this log–log plot does not reveal a strict linear relationship, but instead a nonlinear relationship, that is, $y = -1.67x^2 + 0.62x - 0.12$. In other words, the connectivity distribution does not reflect a strict power law. The same applies for the Munich network (figure 5) and the San Francisco network (figure 6).



(a) (b)

Figure 5. Munich—Linear scale plot connectivity versus cumulative probability (a) and log–log scale plot connectivity versus cumulative probability (b).



(a) (b)

Figure 6. San Francisco—linear scale plot connectivity versus cumulative probability (a) and log–log scale plot connectivity versus cumulative probability (b).

5.2 Small-world properties

The second part of our analysis concerns the evaluation of small-world behaviours in urban street networks. We calculated the average path length and clustering coefficient of three city networks, as shown in the columns L_{actual} and $C^{(1)}_{\text{actual}}$ of table 3.

Table 3. Calculation results.

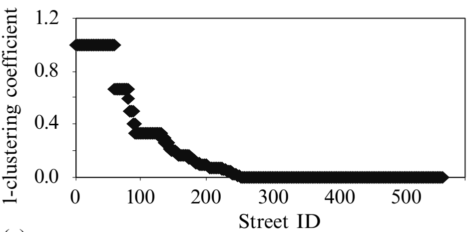
City	Streets	$\bar{m}$	L_{actual}	L_{random}	$C^{(1)}_{\text{actual}}$	$C^{(1)}_{\text{random}}$
Gävle	565	4.00	6.048	4.785	0.188	0.007
Munich	785	4.76	6.319	4.271	0.215	0.006
San Francisco	637	7.50	3.520	3.229	0.142	0.012

For comparison purposes, we calculated the two measures for a random graph with the same number of nodes and connectivity per vertex ($\bar{m}$) in the columns of L_{random} and $C^{(1)}_{\text{random}}$. They are approximately given by $L_{\text{random}} = \ln n / \ln m$, and $C^{(1)}_{\text{random}} = \bar{m}/n$, respectively, where n is total number of vertices of the random graph, and $\bar{m}$ is average number of edges per vertex (Watts and Strogatz, 1998).

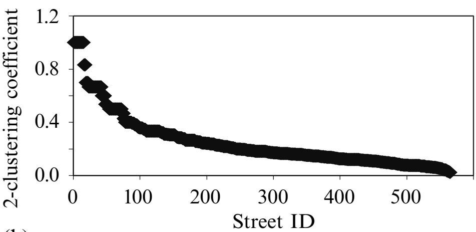
The calculated results show that all three networks have small degrees of separation, that is, the average separation between any two randomly chosen streets is less than 7 in all cases. This means that on average any two streets are just a few streets apart. In addition, clustering coefficients for the three cities meet the condition $C \gg C_{\text{random}}$, with 27-fold, 36-fold, and 12-fold for the Gävle, Munich, and San Francisco networks, respectively. These two results reveal the fact that these street networks are small-world networks.

5.3 Distribution of the 2-clustering coefficient

The third part of our analysis concerns the distribution of the 2-clustering coefficient among the streets of the three case-study cities. Figures 7, 8, and 9 (over) show the distribution of 1-clustering and 2-clustering coefficients. These figures show that the 2-clustering coefficient is more smoothly distributed than the 1-clustering coefficient in these three networks. It should be noted that in these figures the x axes represent the sorted sequence of streets per reverse order of 1-clustering and 2-clustering coefficient values with respect to (a) and (b). Because of this fact, no correlation exists between the

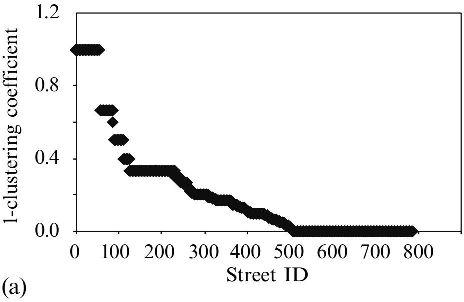


(a)

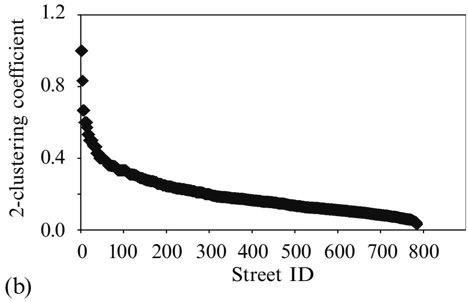


(b)

Figure 7. Gävle—distribution of (a) 1-clustering coefficient and (b) 2-clustering coefficient of streets.



(a)



(b)

Figure 8. Munich—distribution of (a) 1-clustering coefficient and (b) 2-clustering coefficient of streets.

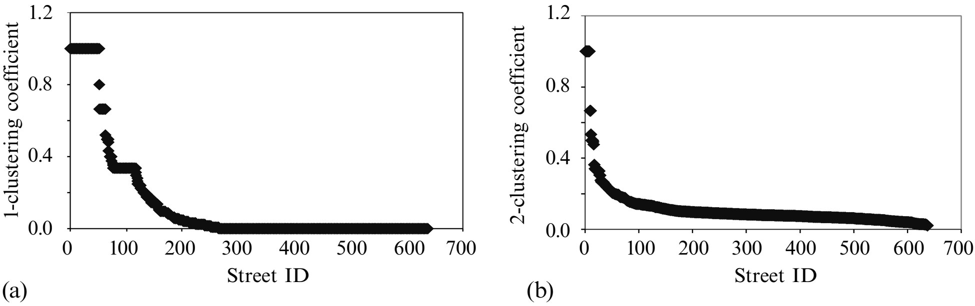


Figure 9. San Francisco—distribution of (a) 1-clustering coefficient and (b) 2-clustering coefficient of streets.

two measures. Furthermore, the smooth distribution reflects the fact that the 2-clustering coefficient can better differentiate clustering degrees among streets.

Log–log scale plots for the 2-clustering coefficient versus cumulative probability show that a strict power law distribution does exist for San Francisco, but not for the two other cities (figures 10, 11, and 12). This reflects the property that, for the majority of streets in San Francisco, their neighbouring streets within 2-neighbourhood are not well interconnected; and for only a few streets, are the neighbouring streets within 2-neighbourhood extremely well interconnected. This property may differentiate grid-like cities from other, irregular, cities.

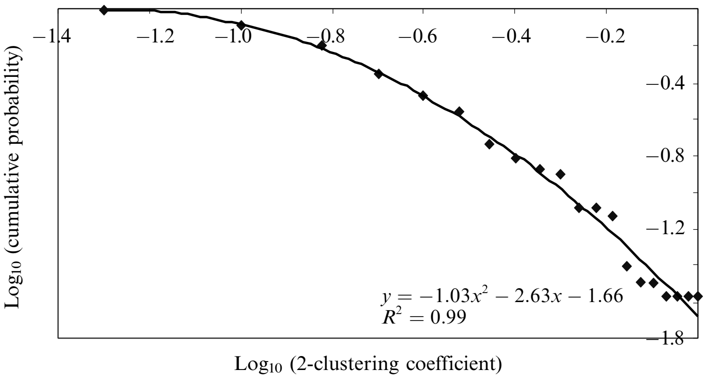


Figure 10. Gävle—log–log scale plot 2-clustering coefficient versus cumulative probability.

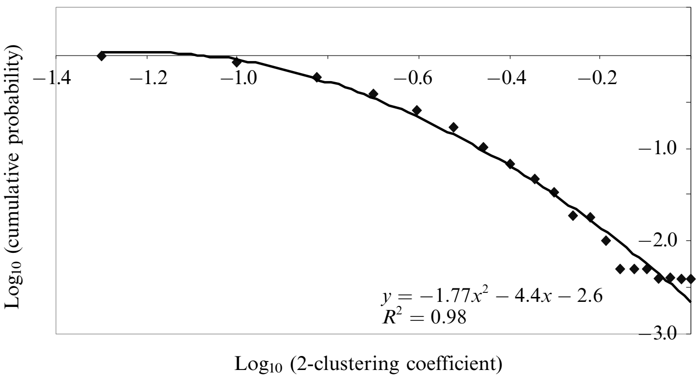


Figure 11. Munich—log–log scale plot 2-clustering coefficient versus cumulative probability.

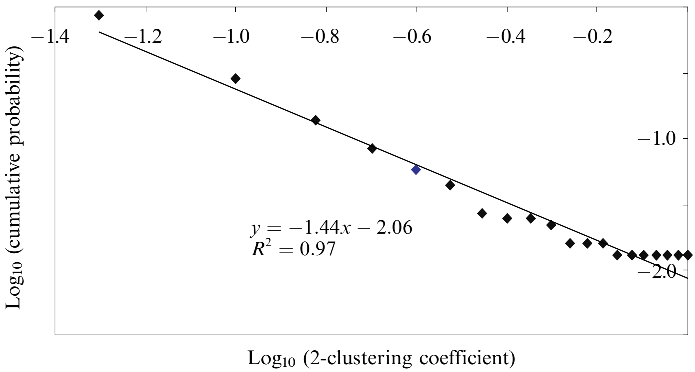


Figure 12. San Francisco—log–log scale plot 2-clustering coefficient versus cumulative probability.

6 Conclusion

The research presented in this paper combines experimental and computational findings. At the experimental level, we describe a topological-based analysis of an urban street network. Two conclusions can be drawn. First, street connectivity does not conform to a strict power-law distribution, and no scale-free property can be seen from the point of view of street connectivity. Second, the topology of street networks reveals a small-world property with a short separation and high clustering coefficient. This presents a nice analogy with small-world networks in the sense that the number of steps required to connect from any street to any other street of a city is in general very small.

From a computational perspective, we introduce a new k-clustering coefficient that generalises the clustering coefficient by including k-neighbours—rather than immediate neighbours only. In particular, our experiment shows that the 2-clustering coefficient can better differentiate the clustering degrees of named streets in a network, and that this coefficient shows power-law distribution in grid-like networks. The preliminary computational experiments show that higher values of k for the k-clustering coefficient ($k > 2$) seem to confirm the properties observed for $k = 2$. There is also a need to generalise the computation of the 2-clustering coefficient to a whole network. Those issues will be addressed in further work.

The topological properties illustrated are of interest to urban studies. For example, this computational approach provides a different perspective from that of urban morphology studies by offering another level of abstraction from those often used in network GIS, as our computational model uses a street-centred modelling view. It should be emphasised that the definition of a 'named street' is rather culture dependent. Our future work should focus on the impact of such cultural artefacts on overall topological properties, for example, whether or not US and European cities demonstrate different topological properties.

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References

Albert R, Jeong H, Barabasi A L, 1999, "Diameter of the World-Wide-Web" *Nature* **401** 130–131
Barabasi A L, 2002 *Linked: The New Science of Networks* (Perseus Publishing, Cambridge, MA)
Barabasi A L, Albert R, 1999, "Emergence of scaling in random networks" *Science* **286** 509–512

Bilke S, Peterson C, 2001, "Topological properties of citation and metabolic networks" *Physical Review E* **64** 036106-1-5
Buckley F, Harary F, 1990 *Distance in Graphs* (Addison-Wesley, Reading, MA)
Cancho R F, Sole R V, 2001, "The small-world of human language" *Proceedings of the Royal Society of London B* **268** 2261 – 2265
Dijkstra E W, 1959, "A note on two problems in connection with graphs" *Numerische Mathematik* **1** 269 – 271
Faloutsos M, Faloutsos P, Faloutsos C, 1999, "On power-law relationships of the internet topology" *ACM SIGCOMM Computer Communication Review* (ACM Press, New York) **29**(4) 251 – 262
Gross J, Yellen J, 1999 *Graph Theory and Its Application* (CRC Press, London)
Hillier B, Hanson J, 1984 *The Social Logic of Space* (Cambridge University Press, Cambridge)
Jeong H, Tombor B, Albert R, Oltvai Z N, Barabasi A L, 2000, "The large-scale organisation of metabolic networks" *Nature* **407** 651 – 654
Kleinfeld J S, 2002, "The small world problem" *Society* **39**(2) 61 – 66
Milgram S, 1967, "The small world problem" *Psychology Today* **2** 60 – 67
Miller H J, Shaw S L, 2001 *Geographic Information Systems for Transportation: Principles and Applications* (Oxford University Press, Oxford)
Montoya J M, Sole R V, 2002, "Small world patterns in food webs" *Journal of Theoretical Biology* **214** 405 – 412
Newman M E J, 2001, "The structure of scientific collaboration networks" *Proceedings of the National Academy of Sciences of the USA* **98** 404 – 409
Scott J, 1999 *Social Network Analysis* (Sage, London)
Shiode N, Batty M, 2000, "Power law distributions in real and virtual worlds", in *INET 2000 Proceedings* http://www.isoc.org/inet2000/cdproceedings/2a/2a_2.htm
Strogatz S, 2001, "Exploring complex networks" *Nature* **410** 268 – 276
Waters N M, 1999, "Transportation GIS: GIS-T", in *Geographical Information Systems, Volume 2* Eds P A Longley, M F Goodchild, D J Maguire, D W Rhind (John Wiley, Chichester, Sussex) pp 827 – 844
Watts D J, 2003 *Six Degrees: The Science of a Connected Age* (W W Norton, Boston, MA)
Watts D J, Strogatz S H, 1998, "Collective dynamics of 'small-world' networks" *Nature* **393** 440 – 442
Zipf G K, 1949 *Human Behavior and the Principles of Least Effort* (Addison Wesley, Cambridge, MA)