

Modelling walking and cycling accessibility and mobility

Walking
and cycling
accessibility
and mobility

The effect of network configuration and occupancy on spatial dynamics of active mobility

101

Pirouz Nourian, Samaneh Rezvani, Kotryna Valeckaite and
Sevil Sariyildiz

*Department of Design Informatics,
Delft University of Technology, Delft, The Netherlands*

Received 30 October 2017
Revised 28 February 2018
Accepted 2 April 2018

Abstract

Purpose – The most sustainable forms of urban mobility are walking and cycling. These modes of transportation are the most environmental friendly, the most economically viable and the most socially inclusive and engaging modes of urban transportation. To measure and compare the effectiveness of alternative pedestrianization or cycling infrastructure plans, the authors need to measure the potential flows of pedestrians and cyclists. The paper aims to discuss this issue.

Design/methodology/approach – The authors have developed a computational methodology to predict walking and cycling flows and local centrality of streets, given a road centerline network and occupancy or population density data attributed to building plots.

Findings – The authors show the functionality of this model in a hypothetical grid network and a simulated setting in a real town. In addition, the authors show how this model can be validated using crowd-sensed data on human mobility trails. This methodology can be used in assessing sustainable urban mobility plans.

Originality/value – The main contribution of this paper is the generalization and adaptation of two network centrality models and a trip-distribution model for studying walking and cycling mobility.

Keywords Social network analysis, Local betweenness centrality, Local closeness centrality, Radiation model, Spatial urban dynamics, Sustainable urban mobility

Paper type Research paper

Introduction

The main focus of this paper is to devise methods and models to formulate and calculate the effect of population density and network configuration on the flow of pedestrian and cyclists. The contributions of this paper are the generalization of two network centrality models and a mobility flux prediction model. As such, the geo-data and demographics presented are merely utilized to illustrate the exemplary use of the proposed methodology and models. In addition, we formulate a computational procedure for validation and/or calibration of the proposed models. For studying spatial dynamics of mobility, some scholars use network centrality indicators as proxies (for both pedestrians and vehicles); examples can be seen in: Blanchard and Volchenkov, 2009; Cooper, 2017; Jiang and Claramunt, 2004; Penn *et al.*, 1998; Porta *et al.*, 2006a, b; Serra and Hillier, 2017; Stähle *et al.*, 2005).

Active mobility

As opposed to other modes of transportation, road congestion is not a problem for walking and cycling mobility, but often a requirement for pedestrians and cyclists to feel safe to walk



© Pirouz Nourian, Samaneh Rezvani, Kotryna Valeckaite and Sevil Sariyildiz. Published by Emerald Publishing Limited. This article is published under the Creative Commons Attribution (CC BY 4.0) licence. Anyone may reproduce, distribute, translate and create derivative works of this article (for both commercial & non-commercial purposes), subject to full attribution to the original publication and authors. The full terms of this licence may be seen at <http://creativecommons.org/licenses/by/4.0/legalcode>

Smart and Sustainable Built
Environment
Vol. 7 No. 1, 2018
pp. 101-116
Emerald Publishing Limited
2046-6099
DOI 10.1108/SASBE-10-2017-0058

or cycle through urban roads. This is what is usually referred to as the critical mass of cyclists required to provide the feeling of traffic/social safety. For this reason, and also to ensure maximum reach/coverage of an intervention in terms of the number of citizens served by an intervention (e.g. a pedestrianization plan, a pedestrian bridge, a bike-sharing network, etc.), we need to be able to predict both the walking/cycling flows and accessibility of locations. For both purposes, networks are ideal abstractions to use as the basis of models because the walkable/cycleable space as a two-manifold[1] can be best discretized as a network in which the costs of traversal can be attributed to the links (Figure 1).

Social-spatial network analysis and urban mobility

Social network analytics provide a theoretical basis for understanding the dynamics of networks by identifying the structural tendencies associated with positions in a network. The reasons for viewing active mobility as a social-spatial network are manifold, namely:

- Geographical space can be best modeled with networks (as opposed to plane maps) because the distance between any two points is almost always considerably larger than the straight-line Euclidean distance due to obstructions; therefore, modal accessibility for active modes of mobility is greatly influenced by network structure.
- Active mobility flows depend on the social ambience of environments, which is arguably influenced by the structural position of spaces within the larger environment. The heterogeneity of structural positions can be very well analyzed by centrality models adopted from social network analytics.

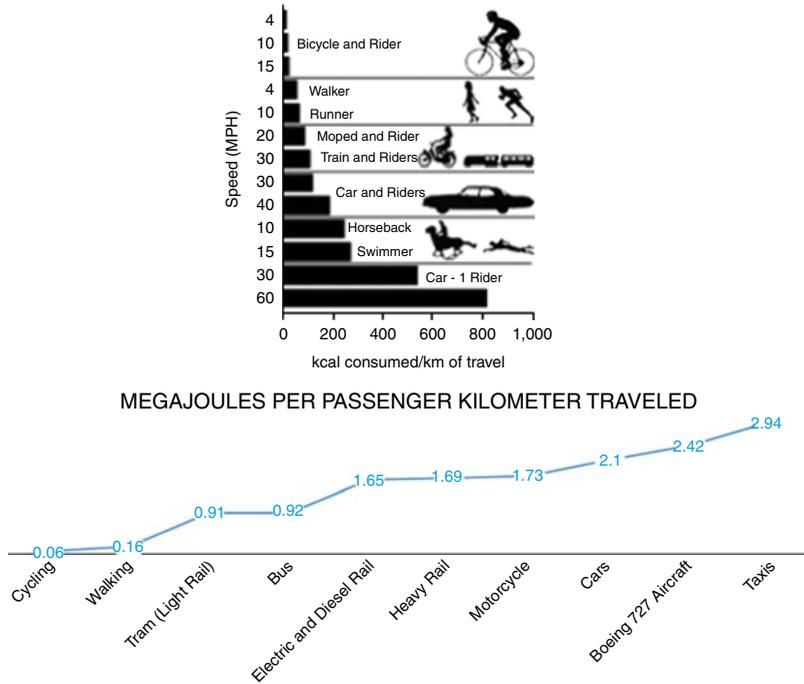


Figure 1.
Energy-efficiency
in transportation

Sources: Based on the data of (Banister, 2009) reproduced from an image of www.treehugger.com, by A.K. Streeter, www.treehugger.com/bikes/trying-travel-city-bikes-are-most-efficient-way-move.html

- The practicality or impracticality of walking or cycling depends on the cognitive complexity of paths and the slope of paths, both of which can be best considered on networks.

Street network and urban population density

There is a scholarly debate on how the structure of networks or the land use (and thus population density) determine the centrality of locations in cities. The theoretical framework of space syntax assumes that it is the configuration of the environment that eventually determines the distribution of land uses and densities (Hillier, 2007). Such a harmony between network structure and land use distribution patterns can be observed in historical city centers and vernacular settlements that have organically evolved. However, in new towns where municipal authorities and planning measures can decide on land-use plans (quite possibly), regardless of the network structure, this assumption might not be correct. In transport planning, the so-called land-use transport interaction models (see Carvalho and Iori, 2008) seek to explain the interrelations between the network and land uses and their effect on the mobility flows. In this paper, we focus on the particularities of active modes of transport and the relation between the walking/cycling flows with both the network structure and the (actual occupants) population density distribution. The assumption behind this approach is that the degree to which a location within a network is a potential origin or a destination is related to the number of people present at that location, i.e. the more the population, the higher the attraction or “radiation.”

Methodology

This paper reports a methodological development, and thus the data presented are for illustrating the functionality of the proposed methods. We propose a methodology to generalize the mobility flux radiation model (Simini *et al.*, 2012) to predict the flow of pedestrians/cyclists on the streets within such neighborhoods. The procedure is as follows (Figure 2):

- (1) enhance the resolution of street networks by homogenizing the segment lengths (shattering street lines into pieces not larger than a certain length) and reducing unnecessary junction points (i.e. cartographic generalization by making topological vertices as representatives of the junction points) (see Figures 3 and 4);
- (2) construct a bipartite topological model in which vertices represent junctions and edges represent streets;
- (3) construct a dual network model where nodes represent streets and links represent junctions;
- (4) compute the graph traversal costs;
- (5) find the easiest paths (from Nourian, van der Hoeven *et al.*, 2015) (Nourian, 2016) between any pair of origin and destination for walking or cycling (within range of acceptable travel-time);
- (6) map the given population (occupation) of the plot to the closest street(s); and
- (7) compute the transition flows between locations within the given range.

Research objectives and research questions

The goal of this research is to provide a foundation for assessing sustainable urban mobility plans in terms of their effectiveness for walking and cycling accessibility improvements. To this end, we propose to utilize a universal mobility flow model generalized for networks.

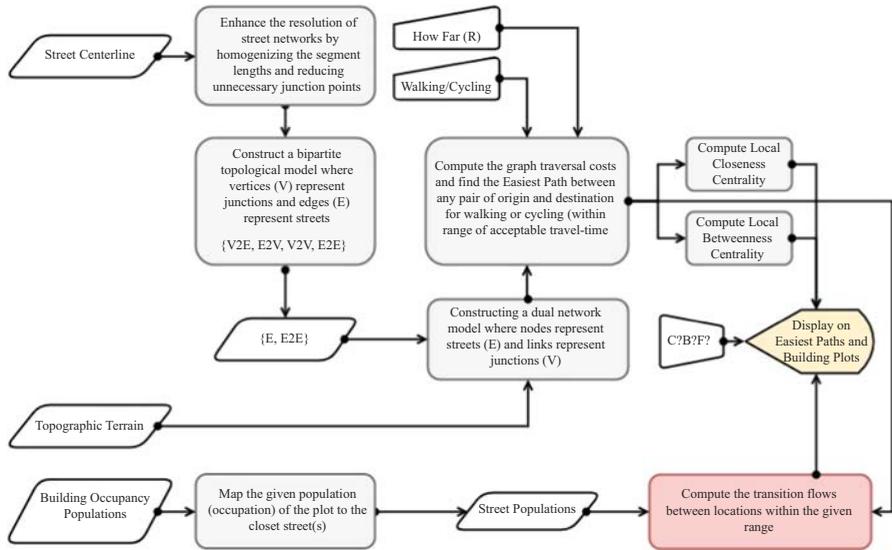


Figure 2. The proposed methodology for analyzing active urban accessibility and mobility in terms of closeness, betweenness and radiation-mobility flows

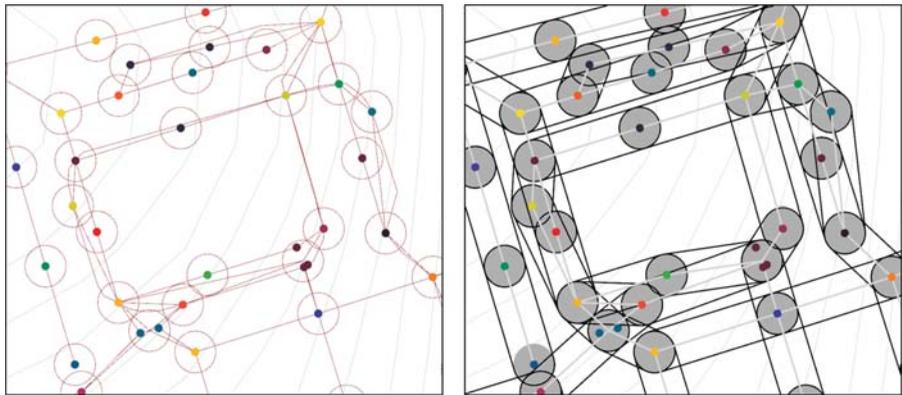


Figure 3. Cartographic generalization and topological modeling of the street network (steps 1 and 2 in the Methodology)

Notes: From left to right, respectively, cartographic generalization, forming vertices as junctions, simplifying junctions as vertices

Thus, the objective of this research is to generalize the so-called universal model of mobility (Simini *et al.*, 2012) from the Euclidean space to network spaces, where distances are calculated through geodesics (optimal paths on network). The matrix of origin–destination distances in such a setting is generally asymmetrical, and all distances $D_{i,j}$ are greater than or equal to the 3D Euclidean distance, i.e. $D_{i,j} \geq L_{i,j}$.

The main questions that this paper answers are:

- RQ1. How to generalize a (mobility flux) radiation model for network spaces?
- RQ2. What is the relation between the generalized (mobility flux) radiation model and social/spatial network centrality models?
- RQ3. How to validate and/or calibrate the generalized (mobility flux) radiation model, given crowd-sensed mobility data?

Network space and network distance

Walking and cycling do not incur costs for a traveler, therefore a natural measure of deterrence for a journey would be the travel-time, provided the physical and cognitive conditions are already considered in computing the minimum travel times. As with any other measure of distance, the distance between two points must be an indicator of the spatial/temporal length of an optimal path or a geodesic. In many urban and regional studies, Euclidean distance is used for measuring the distances and accessibilities. Arguably, the importance of difference between Euclidean distance and network distance in large scales fades away. This is shown, for example, in the study of simplest paths (Duckham and Kulik, 2003) and a comparison of urban network analysis methods (Sevtsuk and Mekonnen, 2012). However, for studying the micro-scale dynamics of walking and cycling mobility, we argue that not only the network space should be the basis of any study, but also the travel-time distance should be used instead of other metrics. Consider two buildings located on opposite sides of a river or an arterial road; for a pedestrian, no matter how close these two locations seem to be in terms of Euclidean distance, the actual walking travel-time distance might be much more than the Euclidean distance. In fact, in built environments, the minimum distance between any two points on the streets is almost always longer than the length of a straight line between those points (Euclidean distance); let alone the extra time wasted for navigation through a complex path.

Local closeness centrality

By computing geodesics between any pair of origin–destination, we can also obtain a matrix of mutual temporal distances between any two points in a network space. Note that for a pedestrian or a cyclist, this distance is not symmetrical, i.e. the distance between A and B might be shorter or longer than B and A. This is because a downhill road is easier to walk than an uphill road; therefore, the travel-time for a downhill path is necessarily less than the travel-time for the same path traversed in the opposite direction. We calculate the local closeness centrality (after Sabidussi, 1966) of every location using the distances computed from easiest paths geodesics in a manner similar to the calculation of local integration in space syntax (Hillier, 2007). Following the fuzzy (Rosyara *et al.*, 2008) definition of closeness given in Nourian (2016), we can put forward a more straight-forward definition of local closeness as “the average closeness to all other location”:

$$C_i^C(R) = \frac{\sum_{j \in \mathbb{A}} C_{ij}^R}{N}, \text{ catchment area} := \mathbb{A} = \{j \in [0, n] | D_{ij} \leq R\}.$$

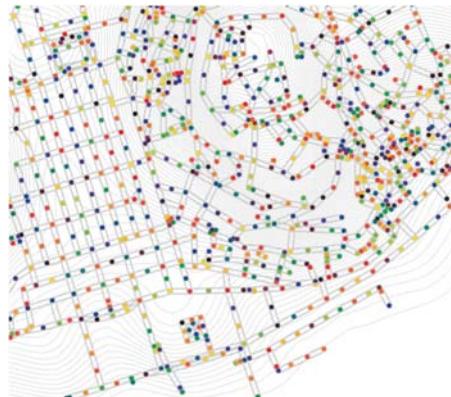


Figure 4. All junctions modeled as vertices, all streets longer than a certain length shattered into pieces, therefore forming new vertices, later modeled topologically as edges of the network (part of the city of Lisbon in this case)

Considering a mode of transportation, we can model the closeness of a location as to the threshold distance above which a traveler's tendency to traverse is inconsiderable. We can model such a closeness value using a sigmoid function:

$$C(x, R) = \frac{1}{1 + e^{\lambda(x - \frac{R}{2})}}$$

where x denotes travel-time distance, λ denotes a limitation coefficient and R denotes the radius above which the perceived convenience or feasibility of traveling with a certain mode of transportation is practically zero; i.e. $\{C(x, R) < \varepsilon | x \geq R\}$. To ensure this feature, we put (Figure 5):

$$\lambda = \frac{2}{R} \ln\left(\frac{1}{\varepsilon} - 1\right).$$

Therefore, we reformulate local (cognitive/fuzzy) closeness centrality as below:

$$C_i^c(R) = \frac{1}{N} \sum_{(j \in A(R))} \left(\frac{1}{1 + e^{\lambda(D_{i,j} - \frac{R}{2})}} \right), A(R) = \{j \in [0, n] | D_{i,j} \leq R\}, \lambda = \frac{2}{R} \ln\left(\frac{1}{\varepsilon} - 1\right)$$

Intuitively, the closeness of any location at nearly zero distance is 1 (100 percent), and the closeness of any location located beyond the acceptable range of travel is nearly 0 (Figure 6).

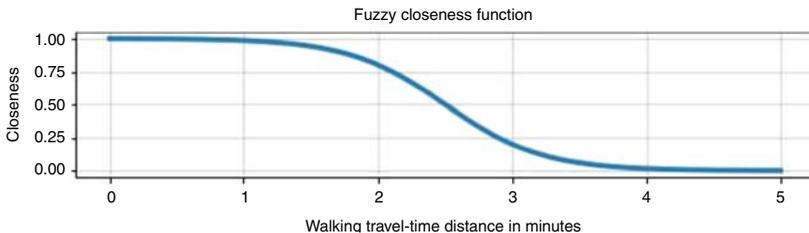
Local betweenness centrality

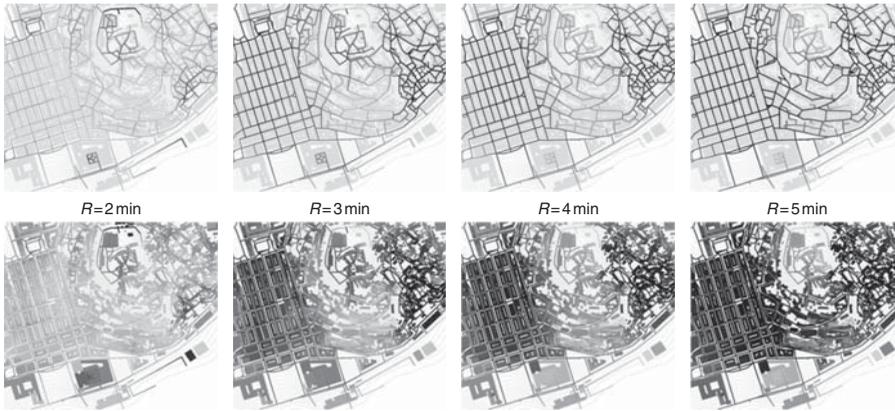
Considering a radius of search, we can generalize betweenness centrality (Freeman, 1977) for a network of nodes and links (usually referred to as vertices and edges) $G(V, E)$ as below, where $\mathcal{G}(s, t)$ denotes the geodesic path between two nodes $\{s, t\}$ (Figure 7):

$$\mathbb{P}(R) = \{\mathcal{G}(s, t) | (s, t \in V) \wedge (s \neq i \neq t) \wedge (D[s, t] < R)\},$$

$$C_i^b(R) = \frac{\sum_{s \in V} \sum_{t \in V} \gamma(s, i, t)}{|\mathbb{P}(R)|}, \gamma(s, i, t) = \begin{cases} 1, & \text{if } \gamma_{st} \ni i \\ 0, & \text{otherwise} \end{cases}$$

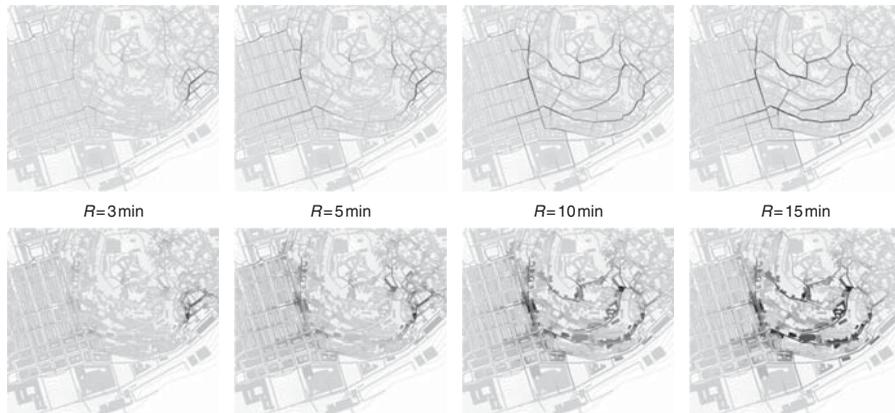
Figure 5. Fuzzy (cognitive) closeness vs distance (Nourian, 2016), for an exemplary pedestrian who is not willing to walk more than 5 minutes for daily commutes, i.e. when $R = 5$





Note: The images on the top show the computed results visualized only on the streets, and the images below show those results projected to the attributed building polygons

Figure 6.
Local fuzzy closeness
centrality; mode of
transport: cycling



Note: The images on the top show the computed results visualized only on the streets, and the images below show those results projected to the attributed building polygons

Figure 7.
Local betweenness;
mode of
transport: walking

The network radiation model of mobility fluxes

The fundamental equation of the radiation model (Simini *et al.*, 2012) is an alternative to the conventional gravity models, often used for “Trip Distribution” in transport modeling (de Dios Ortúzar and Willumsen, 2011). Gravity models are also used for modeling migration/mobility patterns and studying spatial interactions:

$$T_{ij} = T_i \frac{m_i n_j}{(m_i + s_{i,j})(m_i + n_j + s_{i,j})}$$

where m_i is the total population of the i th location, n_j is the total population of the j th location, $S_{i,j}$ is the total population in the circle of radius $R_{i,j} = D_{i,j}$ centered at i (excluding the source and destination population), T_i is the total number of commuters that start their journey from the i th location, i.e. $T_i = \sum_{i \neq j} T_{ij}$, which is proportional to the population of the source location; hence $T_i = m_i(N_c)/(N)$, where N_c is the total number of commuters and N is the total population in the country.

This means we can rewrite the equation of the radiation model as follows:

$$T_{i,j} = m_i \left(\frac{N_c}{N} \right) \frac{m_i n_j}{(m_i + S_{i,j})(m_i + n_j + S_{i,j})} \xrightarrow{\text{yields}} T_{i,j} \propto \frac{m_i^2 n_j}{(m_i + S_{i,j})(m_i + n_j + S_{i,j})}$$

Without knowing the actual number of commuters (the N_c), we can safely assume that the portion N_c/N is equal to 1. The reason is that we are after the statistical distribution of flows and not the actual number of individual commuters. In other words, the statistical distribution pattern will be the same regardless of this scalar coefficient. Therefore, effectively, we consider this proportionality as an equality. In order to generalize this model of transition flows, we take the following steps:

- (1) generalize the notion of search radius from Euclidean distance to network geodesic distance;
- (2) change the nature and the unit of distance from spatial (meters) to temporal (minutes);
- (3) generalize the search circle centered at the origin to a “catchment area” from that origin;
- (4) prove that the transition flux to locations beyond the specified reach of a location can be safely ignored and assumed to be zero;
- (5) specify a minimum buffer for a model to avoid the so-called “network edge effects”;
- (6) map the (occupancy) population of locations onto network locations; and
- (7) develop a procedure to compute transition flows in an urban street network.

Using a street-to-street network model (similar to those of Batty, 2004; Hillier and Hanson, 1984; Jiang and Liu, 2009; Porta *et al.*, 2006a; Turner, 2007; Turner and Dalton, 2005), we model the distance from every street segment to all other street segments, by means of easiest paths (Nourian, van der Hoeven *et al.*, 2015), considering the cognitive impedance of path complexity, the physical impedance of slopes for pedestrians or cyclist and the length of the paths. Using this methodology, we compute an asymmetrical matrix of distances $[D_{i,j}]$ containing temporal walking/cycling distances between any possible pair of origins and destinations within the network. This model provides for the first three steps of the generalization.

Here we explain and prove that the transition fluxes to destinations beyond the accepted range of travel can be safely ignored as being equal to zero. First, observe that for a traveler, there are infinitely many locations beyond reach, but only a countable number of locations within reach, i.e. within a catchment area.

We can verify this by considering the inverse of the closeness function (Nourian, 2016):

$$x = (\text{logit}(C(x)) - 0.5\lambda R) / \lambda.$$

Therefore, when the perceived closeness of a location approaches zero, it can be any location farther than the reach range, even infinitely far away, that is:

$$\lim_{C(x) \rightarrow 0} \frac{\ln\left(\frac{1-C(x)}{C(x)}\right) - \lambda \frac{R}{2}}{\lambda} = \lim_{C(x) \rightarrow 0} \frac{1}{0.5\lambda} \ln\left(\frac{1}{C(x)}\right) = \infty.$$

Now, considering the distance $x = D_{i,j}$ we formally define $S_{i,j}$ in terms of the population within a catchment area, in which P_k denotes the (projected) population of a location:

$$S_{i,j} = \left\{ \sum_{k \in [0,n]} P_k | (D_{i,k} \leq D_{i,j})^{(k \neq i)(k \neq j)} \right\}.$$

Therefore, if $D_{i,j}$ approaches infinity, the number of k th destinations fitting to the above conditions will be infinitely many, going beyond the boundaries of the network; and so, the sum of populations will be virtually unbounded and thus approach infinity, i.e. $\lim_{D_{i,j} \rightarrow \infty} S_{i,j} = \infty$. Hence:

$$\lim_{D_{i,j} \rightarrow \infty} T_{i,j} = \lim_{D_{i,j} \rightarrow \infty} \frac{m_i^2 n_j}{(m_i + S_{i,j})(m_i + n_j + S_{i,j})} = \lim_{D_{i,j} \rightarrow \infty} \frac{m_i^2 n_j}{S_{i,j}^2} = 0.$$

Therefore, we conclude that we can safely assume $T_{i,j} = 0$ when $D_{i,j} > R$, this is because for a traveler (pedestrian/cyclists) any destination beyond reach is considered infinitely far away.

If we consider a metric buffer large enough to ensure that its equivalent travel-time is larger than R , then the model shall not suffer from the so-called network “edge effects” (Gil, 2017). To convert Euclidean distance to travel-time distance for walking/cycling, we adopt the equations (from Tobler, 1970; Nourian, 2016):

$$\boxed{D^W(\delta, \alpha) = \frac{3.6\delta e^{3.5|\tan \alpha + 0.05|}}{6}} \xrightarrow{\text{yields}} D^W(\delta, 0) = \frac{3.6\delta e^{3.5|0.05|}}{6} = 0.7147\delta \text{ sec} = 0.0119\delta \text{ min}$$

$$\boxed{D^C(\delta, \alpha) = \frac{\delta(85 \times 9.81 \times \sin \alpha + 25)}{112}} \xrightarrow{\text{yields}} D^C(\delta, \alpha) = \frac{25\delta}{112} = 0.2232\delta \text{ sec} = 0.0037\delta \text{ min}$$

In which, δ denotes metric distance (displacement), α denotes slope and $D^m(\delta, \alpha)$ denotes (modal: walking or cycling) travel-time distance. This means, to ensure a large-enough buffer, we can rely on the inverse of these functions:

$$\boxed{\delta^W(D) = 83.94D \text{ min}}$$

$$\boxed{\delta^C(D) = 268.8D \text{ min}}$$

These two functions can be interpreted as:

- the typical pace of walking on a flat terrain is nearly 84 meters per minute;
- the typical pace of cycling on a flat terrain is nearly 269 meters per minute; and
- a typical reach range for a cyclist is nearly 3.2 times more than that of a pedestrian for the same travel-time.

Using appropriate multiples of these values to enlarge the extents of a map, we can ensure that the model shall not suffer from the so-called edge effects because in presence of any terrain, the actual walking/cycling distances will be larger than those assumed.

In order to visualize, understand and analyze the results of the radiation model, we need to attribute the transition flows to some kind of arcs, lines or in general geodesics in between every two points. At the same time, we need to compute the catchment populations in order

to compute the flows in between two points. We compute the flows and attribute them to the network geodesics between all pairs of origin–destination. However, before proceeding with the flow computations, we must find out how the populations values can be attributed to locations outside of the network space (typically building polygons) are attributed to and indexed as to the locations on the network (nodes). For such an attribution, we follow two procedures to find, respectively:

- (1) which street segments (L) are closest to which building polygons (P); and
- (2) which building polygons (P) are closest to which street segments (L).

Exemplary results

In this section, we show exemplary results of the algorithms in order to illustrate their functionality (Figure 8).

We have verified that the network radiation model works in a network space. To illustrate the steps taken in verification, we show how the network radiation model works on a on a symmetrical regular grid. These results clearly verify the proper functionality of the model.

Interpreting the results of the network radiation model on Lisbon requires a statistical analysis. It is even visually clear that in the case of the hypothetical homogenous grid network, the radiation flows correspond directly to the distribution of population; however, in the case of the heterogeneous network (Lisbon), it appears that the distribution of flows does not significantly change in spite of the change in the distribution of population. By statistically inspecting the four numerical distributions of flows in the four hypothetical population distributions, we can see that indeed the distributions are nearly the same and that they are all in the form of power-law distributions. This is indeed an interesting phenomenon that can be interpreted as the high influence of network configuration on mobility fluxes; however, to draw such conclusions, further studies are needed to validate the model.

In Figures 9 and 10, we have shown four hypothetical distributions of a fictitious population of 10,000 people for the depicted area in Lisbon and simulated flows of pedestrians and cyclists, respectively. In Figure 11, we show the statistical distributions of pedestrian flows. As also evident from Table I and Figure 11, the distributions are very similar.

Data analytics

In this section, we suggest some generic methods for testing, validating and calibrating the proposed models and methods. We have chosen to illustrate exemplary results on a 1 square

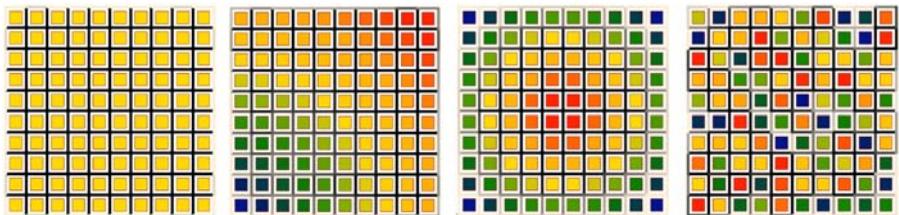


Figure 8.
The exemplary results of the radiation model on a hypothetical grid network

Notes: From left to right, with a uniform distribution of population on building plots, with a uniform distribution of populations from southeast to northwest, with a bell-like distribution, with a random distribution (the warmer the colors, the higher the populations). The street flows are depicted by shades of gray; the darker the color, the higher the flow

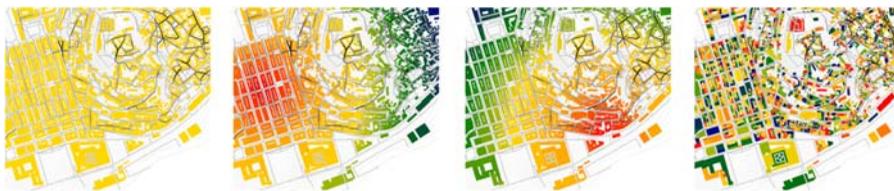
km-sized map of Lisbon, especially because of the considerably hilly landscape of the city. However, if the topographic terrain is negligible, the methods can be applied in an analogous way. In the absence of a topographic terrain, the matrix of distances between origins and destinations will be a symmetric matrix. Note that our method ignores the directional limitations imposed on cycling movements as well as traffic lights, climatic conditions, pavement quality, presence of stairs, etc.

Geo-data: street lines and building polygons

The main geo-data inputs required for the proposed models include street centerlines, building polygons and (optionally) topographic terrain models as digital terrain models (DTM) or digital elevation model. Street centerline and building polygon data can be acquired from OpenStreetMap (OSM) or governmental geo-data sets. The topographic terrain model needed for the models must be provided as a triangulated irregular network or a polygon mesh; however, the DTM models are often available as raster models. The raster models can be used to generate 3D points, from which, using Delaunay triangulation, a terrain model can be generated.

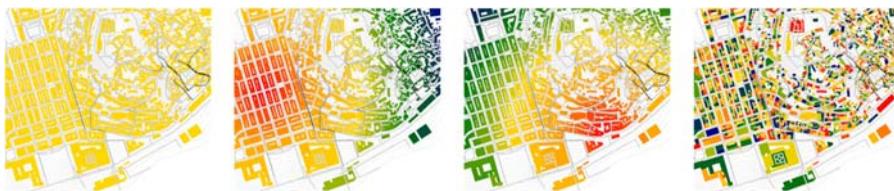
Demographics: estimating population density or occupancy

The census data are almost always too coarse (spatially) to be of use in any model for walking/cycling mobility. Due to privacy considerations, the population census statistics are not provided per building, but they are aggregated per larger area units (e.g. postcode zones). However, as for pedestrians and cyclists, the distances that might be short for car riders might be quite long; therefore, fine resolution occupancy data are needed for making walking/cycling models. Besides, the typical population data from census only consider the dwellers as the population, but in prediction of pedestrian/cyclist fluxes, we need to work with the occupants. For this reason, working with some indicator of the actual occupancy rate is suggested for obtaining population counts for the network radiation model. For instance, the actual energy consumption values or usage data from a cellular communication network might give a better indication of occupancy than the population data alone from the census.



Note: The warmer the color, the more the population

Figure 9.
Local pedestrian
flows, given different
hypothetical
(occupancy)
populations



Note: The warmer the color, the more the population

Figure 10.
Local cyclist flows,
given different
hypothetical
(occupancy)
populations

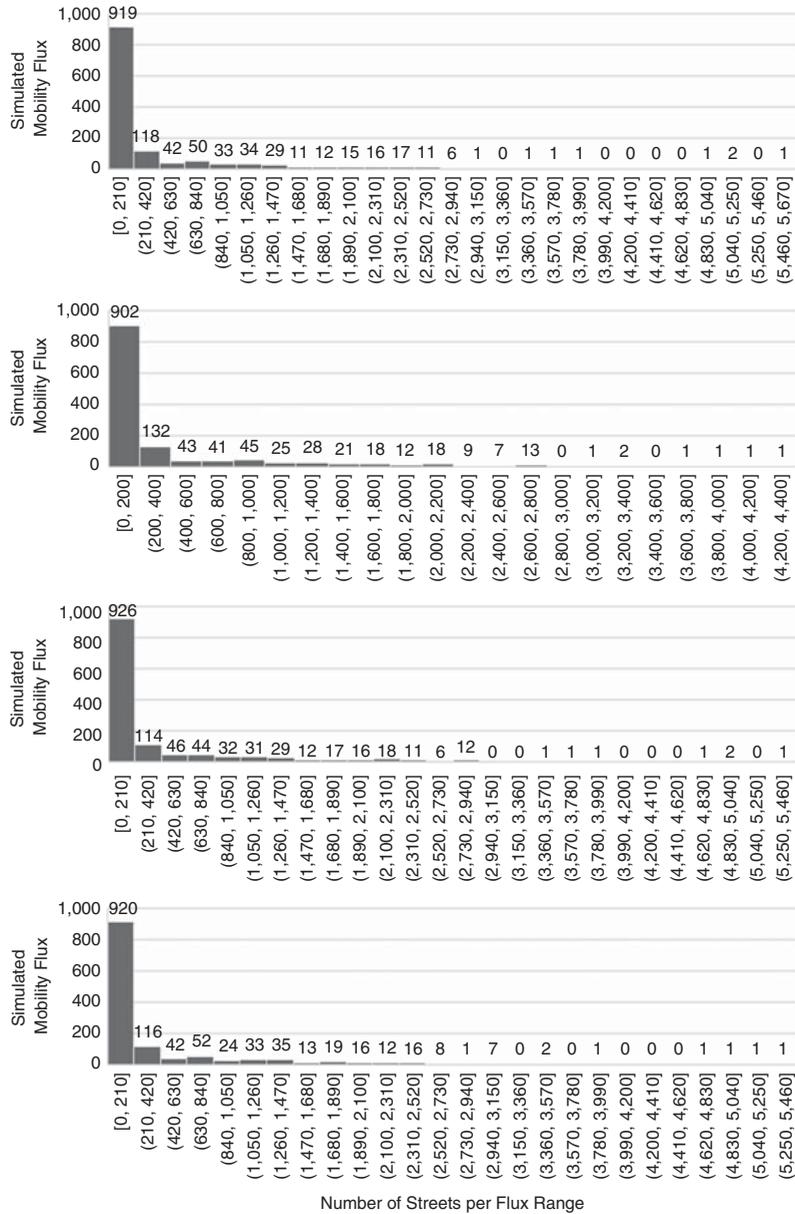


Figure 11. Histograms of simulated mobility fluxes (number of pedestrians) for 1,321 streets in the Lisbon network

Notes: From the top, for hypothetical population distributions, Uniform, West-Center, South Center and Random, respectively (shown previously)

As an example, we can refer to the public open data of annual average electricity and gas consumption data for polygons (separately for residences (woningen) and businesses (bedrijven)) identified by postcodes in the Netherlands provided as open data by the Dutch Government (on PDOK) and the coarse resolution population data provided

Uniform	West-Center	South-Center	Random
Mean	369.1617	Mean 355.8446	Mean 366.1829
SE	18.28717	SE 16.87647	SE 18.23119
Median	91.24477	Median 95.4273	Median 87.82151
Mode	0	Mode 0	Mode 0
SD	664.6575	SD 613.3848	SD 662.6228
Sample variance	441,769.6	Sample variance 376,241	Sample variance 439,069
Kurtosis	11.66015	Kurtosis 7.673449	Kurtosis 10.67179
Skewness	3.026711	Skewness 2.655037	Skewness 2.950699
Range	5,511.152	Range 4,304.772	Range 5,330.66
Minimum	0	Minimum 0	Minimum 0
Maximum	5,511.152	Maximum 4,304.772	Maximum 5,330.66
Sum	487,662.6	Sum 470,070.7	Sum 483,727.6
Count	1,321	Count 1,321	Count 1,321
Largest(1)	5,511.152	Largest(1) 4,304.772	Largest(1) 5,330.66
Smallest(1)	0	Smallest(1) 0	Smallest(1) 0
Uniform	1	West-Cent	South-Cent
West-Cent	0.988247	1	Random
South-Cent	0.997574	0.987464	1
Random	0.996846	0.985114	0.995889

Table I.
Descriptive statistics
of simulated mobility
flows for pedestrians,
using the network
radiation model

for the chosen district (“*Buurt*” in Dutch). It can be assumed that the number of people living/working in an address on an average annual basis is correlated with the consumption of gas and electricity. The consumption of gas is measured in terms of cubic meters and the consumption of electricity is measured in terms of kilo watt hours. These values are incommensurate, and so, they cannot be added together, but we can multiply the two values to get an indication of the intensity of use of space. Knowing the average electricity and gas consumption values per person for residents and employees, we can possibly estimate the occupancy population of the building polygons. Such estimates can be adjusted and checked against the resident population of the district polygons (Buurten).

Data collection and validation of mobility models

We suggest a procedure such as the one proposed in (Sileryte *et al.*, 2016) for collecting the annual average of walking or cycling GPS trails for validating our mobility models. This procedure, briefly, can be explained as extracting the GPS trails every eight days within a year so that different days, seasons, weather conditions and other factors possibly influencing mobility are sampled without bias. Then the number of times a trail falls through a “street segment” is counted. It must be noted that the spatial structure of GPS tracks is so that they refer to Euclidean space, i.e. a GPS trail consists of position coordinates. However, in validating or calibrating a spatial model whose space is a network space, any such trail must be first projected to the relevant nodes on the network (streets). For this very reason, a dual network model (street–street interconnections) such as the one proposed here can work better than a primal network model (junction–junction interconnections). This way, the number of times a certain street segment is used on an annual average basis is counted. The distribution of these counts can be statistically compared against the distribution of flows from our models (e.g. local betweenness centrality or network radiation). Such statistical comparisons provide for validation or calibration of network mobility models.

Implementation

The algorithms are implemented in Microsoft .NET framework, using the C# language. Geometric algorithms are based on Rhinocommon.dll that is the kernel of Rhino3D (McNeel, 2017); visualization and tests have been done on Grasshopper3D (Rutten, 2007); the easiest paths are found using the toolkit Configurbanist (Nourian, Rezvani, *et al.* 2015). The geo-data from OSM are harvested using the toolkit Elk (Logan, 2012). Numerical calculations have been performed using Accord.NET (de Souza, 2014).

Conclusion

The proposed analytic models can be used in assessing sustainable urban mobility planning scenarios such as pedestrianization and cycling infrastructure design, primarily to measure the effectiveness of proposed interventions in terms of accessibility and mobility potentials. For instance, such methods can be used in order to find out whether a new plan for a set of bike-sharing stations is well laid out in terms of accessibility of stations, as in, for example, how many people will be served in the 3-minute walking catchment area of these stations, especially in comparison with an alternative, or to find out how effective it could be to add a pedestrian bridge over a river/valley and where would be best to place that bridge to ensure highest achievable effect. The complexity of accessibility and mobility for walking and cycling is twofold: on one hand, the physical complexity of the urban networks affects the distances and the physical ease of walking and cycling, and on the other hand, the cognitive complexity of the environment affects both the perception of accessibility and the choice of walking and cycling as the preferred mode of transportation. We have used a model of easiest paths to encompass the cognitive complexity of way-finding in our models. However, the entirety of accessibility and mobility is in reality much more intricate that can be possibly modeled mathematically; this is because in reality, many factors play a role in shaping actual flows of people, namely, climatic conditions, pavement quality, particular/contextual attraction or repulsion of destinations, scenic quality of places, etc. (some of which might be possibly taken into account in modeling mobility). Nevertheless, in urban planning, it is desirable to have models that can explain and thus predict the long-term effect of potential interventions (not on an individual but on a typical citizen), models that can explain the spatial dynamics of a city. These models will be, by definition, abstract simplified versions of reality, whose purpose is not only to predict the spatial dynamics, but also to explain their underlying mechanisms.

We have generalized the radiation flow model of trip distribution for walking and cycling on networks. The network radiation model needs to be validated and calibrated using actual mobility data. Such data can be harvested from crowd-sourced mobility trails collections. The model is verified in terms of providing plausible results (as apparent from its application on a regular grid). A preliminary conclusion from the exemplary results of the network radiation model could be that the flow of pedestrians and cyclists (at least as simulated with this model) is to a large extent determined merely by the configuration of the network itself, rather than the distribution of population. However, for interpreting the implications of the model predictions in real-world urban contexts, such as the ones shown on Lisbon, a larger statistical analysis is needed and suggested for future research.

Note

1. A topological space that is everywhere locally similar to a Euclidean space of dimension 2; definition adopted from: <http://mathworld.wolfram.com/Manifold.html>

References

- Banister, D. (2009), "Sustainable transport and public policy", *Transport Engineering and Planning*, Vol. II, pp. 192-214, available at: <https://pdfs.semanticscholar.org/e95a/f150c0648610948f1c5a73549815ef4603e3.pdf>
- Batty, M. (2004), "A new theory of space syntax", CASA Working Paper Series No. 44, available at: <http://discovery.ucl.ac.uk/2111/1/paper75.pdf>
- Blanchard, P. and Volchenkov, D. (2009), *Mathematical Analysis of Urban Spatial Networks*, Springer, available at: <https://doi.org/10.1007/978-3-540-87829-2>
- Carvalho, R. and Iori, G. (2008), "Socioeconomic networks with long-range interactions", *Physical Review E – Statistical, Nonlinear, and Soft Matter Physics*, Vol. 78 No. 1, pp. 1-18, available at: <https://doi.org/10.1103/PhysRevE.78.016110>
- Cooper, C.H.V. (2017), "Using spatial network analysis to model pedal cycle flows, risk and mode choice", *Journal of Transport Geography*, Vol. 58, pp. 157-165, available at: <https://doi.org/10.1016/J.JTRANGEO.2016.12.003>
- de Dios Ortúzar, J. and Willumsen, L. (2011), "Modelling transport", available at: https://books.google.nl/books?hl=en&lr=&id=qWa5MyS4CiwC&oi=fnd&pg=PT7&dq=+Dios+Ortuzar,+Juan+de+%26+Willumsen,MODELLING+TRANSPORT&ots=tuZkYe3yZD&sig=DyTN-DvGV__fEXQleaJv3O4q8IU
- de Souza, C.R. (2014), "Accord.NET machine learning framework", available at: <http://accord-framework.net/>
- Duckham, M. and Kulik, L. (2003), "'Simplest' paths: automated route selection for navigation", in Sabine, T., Kuhn, W. and Worboys, M.F. (Eds), *Proceedings of COSIT 2003: Spatial Information Theory. Foundations of Geographic Information Science*, pp. 169-185, available at: https://doi.org/10.1007/978-3-540-39923-0_12
- Freeman, L.C. (1977), "A set of measures of centrality based on betweenness", *Sociometry*, Vol. 40 No. 1, pp. 35-41, available at: <https://doi.org/10.2307/3033543>
- Gil, J. (2017), "Street network analysis 'edge effects': examining the sensitivity of centrality measures to boundary conditions", *Environment and Planning B: Urban Analytics and City Science*, Vol. 44 No. 5, pp. 819-836, available at: <https://doi.org/10.1177/0265813516650678>
- Hillier, B. (2007), "Space is the machine Bill Hillier", Space Syntax, available at: <http://discovery.ucl.ac.uk/3881/1/SITM.pdf>
- Hillier, B. and Hanson, J. (1984), *The Social Logic of Space. The Social Logic of Space*, Cambridge University Press, available at: <https://doi.org/http://dx.doi.org/10.1017/CBO9780511597237>
- Jiang, B. and Claramunt, C. (2004), "Topological analysis of urban street networks", *Environment and Planning B*, Vol. 31 No. 1, pp. 151-162, available at: <http://epb.sagepub.com/content/31/1/151.short>
- Jiang, B. and Liu, C. (2009), "Street-based topological representations and analyses for predicting traffic flow in GIS", *International Journal of Geographical Information Science*, Vol. 23 No. 9, pp. 1119-1137, available at: <https://doi.org/10.1080/13658810701690448>
- Logan, T. (2012), "Elk", available at: www.food4rhino.com/; www.food4rhino.com/app/elk
- McNeel (2017), "Rhino3D", available at: www.rhino3d.com/
- Nourian, P. (2016), "Configraphics: graph theoretical methods for design and analysis of spatial configurations", available at: <https://doi.org/10.7480/abe.2016.14.1348>
- Nourian, P., van der Hoeven, F., Rezvani, S. and Sariyildiz, S. (2015), "Easiest paths for walking and cycling: combining syntactic and geographic analyses in studying walking and cycling mobility", *Proceedings of the 10th International Space Syntax Symposium*, pp. 1-15.
- Nourian, P., Rezvani, S., Sariyildiz, S., Van Der Hoeven, F., Finding, P., Accessibility, F. and Design, C. (2015), "Configurbanist: urban configuration analysis for walking and cycling via easiest paths", *Real Time – Proceedings of the 33rd eCAADe Conference*, Vol. 1, pp. 553-564.

- Penn, A., Hillier, B., Banister, D. and Xu, J. (1998), "Configurational modelling of urban movement networks", *Environment and Planning B: Planning and Design*, Vol. 25 No. 1, pp. 59-84, available at: <https://doi.org/10.1068/b250059>
- Porta, S., Crucitti, P. and Latora, V. (2006a), "The network analysis of urban streets: a dual approach", *Physica A: Statistical Mechanics and Its Applications*, Vol. 369 No. 2, pp. 853-866, available at: <https://doi.org/10.1016/j.physa.2005.12.063>
- Porta, S., Crucitti, P. and Latora, V. (2006b), "The network analysis of urban streets: a primal approach", *Environment and Planning B: Planning and Design*, Vol. 33 No. 5, pp. 705-725, available at: <https://doi.org/10.1068/b32045>
- Rosyara, U.R., Vromman, D. and Duveiller, E. (2008), "Canopy temperature depression as an indication of correlative measure of spot blotch resistance and heat stress tolerance in spring wheat", *Journal of Plant Pathology*, Vol. 90 No. 1, pp. 103-107, available at: [https://doi.org/10.1016/S0019-9958\(65\)90241-X](https://doi.org/10.1016/S0019-9958(65)90241-X)
- Rutten, D. (2007), "Grasshopper3D", available at: www.grasshopper3d.com/
- Sabidussi, G. (1966), "The centrality index of a graph", *Psychometrika*, Vol. 31 No. 4, pp. 581-603, available at: <https://doi.org/10.1007/BF02289527>
- Serra, M. and Hillier, B. (2017), "Spatial configuration and vehicular movement", available at: www.11ssslisbon.pt/docs/proceedings/papers/122-2.pdf
- Sevtsuk, A. and Mekonnen, M. (2012), "Urban network analysis. A new toolbox for ArcGIS", *Revue Internationale de Géomatique*, Vol. 22 No. 2, pp. 287-305, available at: <https://doi.org/10.3166/rig.22.287-305>
- Sileryte, R., Nourian, P. and van der Spek, S. (2016), "Modelling spatial patterns of outdoor physical activities using mobile sports tracking application data", *Geospatial Data in a Changing World*, pp. 179-197, available at: https://doi.org/10.1007/978-3-319-33783-8_11
- Simini, F., González, M.C., Maritan, A. and Barabási, A.-L. (2012), "A universal model for mobility and migration patterns", *Nature*, Vol. 484 No. 7392, pp. 96-100, available at: <https://doi.org/10.1038/nature10856>
- Ståhle, A., Marcus, L. and Karlström, A. (2005), "Place syntax – geographic accessibility with axial lines in GIS", *Proceedings 5th International Space Syntax Symposium*, No. 1994, pp. 131-144, available at: <https://doi.org/10.1.1.1.109.678>
- Tobler, W.R. (1970), "A computer movie simulating urban growth in the Detroit Region", *Economic Geography*, Vol. 46, June, pp. 234-240, available at: <https://doi.org/10.2307/143141>
- Turner, A. (2007), "From axial to road-centre lines: a new representation for space syntax and a new model of route choice for transport network analysis", *Environment and Planning B: Planning and Design*, Vol. 34 No. 3, pp. 539-555, available at: <https://doi.org/10.1068/b32067>
- Turner, A. and Dalton, N. (2005), "A simplified route choice model using the shortest angular path assumption", *Proceedings of the 8th International Conference on GeoComputation, Ann Arbor, MI*, available at: <http://discovery.ucl.ac.uk/39855/>

Corresponding author

Pirouz Nourian can be contacted at: p.nourian@tudelft.nl

For instructions on how to order reprints of this article, please visit our website:

www.emeraldgroupublishing.com/licensing/reprints.htm

Or contact us for further details: permissions@emeraldinsight.com