The effect of spatial configuration on vehicular movement patterns: City of Rotterdam test case

R.H.B. Vos

TU Delft

The effect of spatial configuration on vehicular movement patterns: City of Rotterdam test case

By

R.H.B. Vos

In partial fulfillment of the requirements for the degree of
Bachelor of Science
Civil Engineering
at the Delft University of Technology
to be defended publicly on Tuesday June 25, 2019 at 11:00 AM.

Student number:	4465512
Project duration:	Apr 23, 2019 – Jun 25, 2019
Department:	TU Delft Department of Transport and Planning
Supervisors:	Dr. Ir. W. Schakel
	Ir. R. Koster
	Ir. B. Mashhoodi

TU Delft

Preface

This report has been written by Ruben Vos for the course CTB3000 Bachelor eindwerk as the final part of the TU Delft civil engineering bachelor program. The course was followed at the TU Delft Department of Transport and Planning. The report contains a scientific research on how the spatial configuration of the street network of the city of Rotterdam effects the movement patterns of vehicles. Spatial configuration can be explained as the way space is organized into a network of different shapes, patterns and 'relations that take into account of other relations in a complex'. (B. Hillier, 2007)

Hereby I want to take the opportunity to thank my supervisors Dr. Ir. Wouter Schakel and Ir. Rolf Koster from the Department of Transport and Planning, and Ir. B. Mashhoodi from the Department of Urbanism, Chair of Environmental Design and Technology at Faculty of Architecture and the Built Environment. Ir. B. Mashhoodi was also one of my teachers during the TU Delft minor 'Neighbourhood of the Future' for the QGIS and Cartography workshops. I also want to thank the peer students that were involved in this course. It was an absolute pleasure to receive their support and feedback during the weekly meetings.

Summary

This report investigates the relation between the spatial configuration of the street network and the vehicular movement patterns in the city of Rotterdam. The space syntax approach is used to measure the closeness and betweenness centrality of individual street segments in relation to all others with different spatial scales and means of distance. The closeness centrality captures the relative to-movement by measuring to what extent a street segment is close to all the other street segment along the shortest paths of the network. The betweenness centrality captures the relative through-movement by counting how often the street segment is traversed by all shortest paths between all sets of segment pairs. (S. Porta et. al, 2009) The network centrality measures have been statistically compared with predicted traffic loads from a traditional four-step macroscopic traffic model by a simple linear regression analysis. The network centrality maps are used to identify which streets are more likely to generate movement by the urban structure without any 'special magnets of attraction'. The linear regression analysis with the sum of the closeness and betweenness centrality confirms the hypothesis that the relative total movement of a street segment is a function of both measures. In other words, the total amount of movement is the combined efforts of movement from trips at their destination (e.g. shops at accessible location) or at their origin (e.g. residential area at less accessible location), and movement from pass-by trips (e.g. arterial roads). The theory and derivation of network centrality measures are explained in the theoretical framework and demonstrated by means of a toy street network.

Moreover there is also an attempt to validate space syntax as a traffic assessment tool at urban scale by applying weighting functions based on road characteristics such as segment length, speed limit and road capacity. Weighting functions can add real life complexity and attractiveness to use a particular road. More research such as a multiple regression analysis should be done to see what other variables in urban areas contribute to a stronger linear relationship. Hence it may be possible to use location-based density and differentiation (e.g. spatial density and functions of nearby buildings and public space) as weighting functions. The same approach can also be applied for pedestrians and cyclist movement patterns with smaller spatial scales. By understanding the evolving human patterns as a result of spatial layout of urban areas; space syntax can become a powerful tool to organise a city's complexity and growth with architectural interventions in context with other fields of discipline.

Table of Contents

1. Introduction

1.1 Problem Statement

Traditional four-step traffic models provide a reliable and powerful tool for estimating traffic conditions with different mobility patterns, modal shares, land-uses and network configurations. The implementation can be time-consuming and relatively costly because they rely on huge production and attraction data of traffic users between distinct areas as shown in chapter 1.5 in this report. In times of extensive urban development there is a need for modelling traffic loads and accessibility at urban scale using more generic data collection.

The space syntax approach defines that the structure of the urban grid has 'independent and systematic effects on movement patterns.' (B. Hillier, 2002) The analysis of spatial configurations are based on mathematical graph theory and network theory. Space syntax was originated by B. Hillier and J. Hanson from Barnett School, UCL in the late 1970's. Space syntax techniques can be used as a supporting tool to identify structural problems in cities and investigate the potential social-effects of development options. Research on network centrality provides not only better understanding of cities but it can also help shaping its growth. (S. Porta et. al, 2009) The configurational models are more frequently used to preliminary assess potential vehicular and pedestrian movement at urban scale but they still lack sufficient validation.

1.2 Research Goal

The research goal can be explained as two-fold. Primarily the research aims to show to what extent vehicular movement is affected by the configuration of the street network and by the different parts of the complex system that are related to the each other. There are three hypotheses to be confirmed. The first hypothesis is that closeness centrality captures the relative to-movement whereas betweenness centrality is a measure for relative through-movement of vehicles. The second hypothesis is that the total vehicular movement can be captured by the sum of betweenness and closeness centrality. Furthermore the research attempts to validate space syntax as a traffic assessment tool. Weighting functions are added to the individual and combined network centralities measures to achieve stronger correlation with the predicted traffic loads from the macroscopic traffic model in the simple linear regression analysis.

1.3 Theoretical Framework

Space Syntax as an Urban Model

The space syntax approach contains a set of theories and techniques for analysing the relation between spatial configuration and human activity patterns. (UCL Space Syntax, 2019) A toy street network will be used to explain these theories and techniques in a stepwise manner. Space syntax allows a creation of an urban model that is principally constructed based on a gravity model with central variables; distance and attraction, and a form of representation of urban space. (Wilson, 2000, L. Marcus et. al, 2017) A road centre line map of the street network can be used as the input data for investigating movement patterns in urban areas (see figure 1). A road centre line map is a representation of the street network where 'geometric features are polylines representing street segments which span between junctions'. (G. Stavroulaki et. al, 2017) Each street segment is represented by a node at its centroid in order to allocate its relative position within the street network according to the graph theory (see figure 2).

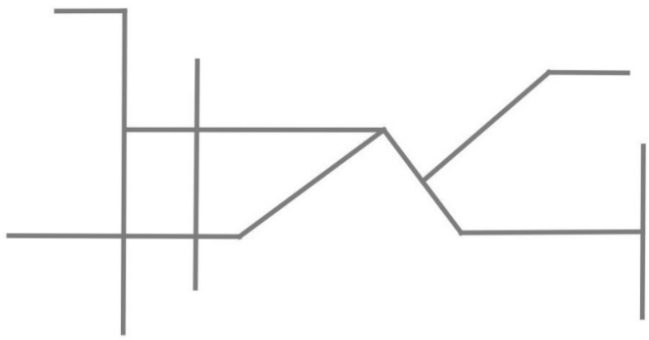


Figure 1, Road Centre Line Map of Toy Street Network

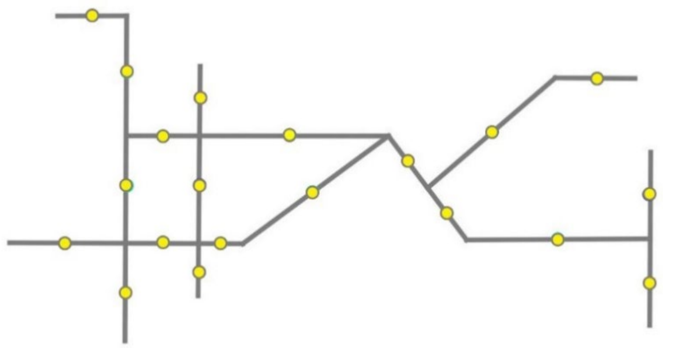


Figure 2, Graph notation of Road Centre Line Map

Network Centrality Measures

The two main measures in space syntax are network centrality measures which are used to examine the two primary all-to-all relations (all street segments to all others) (A. Van Nes, 2014):

- Closeness centrality (or 'integration' as it is called in space syntax)
- Betweenness centrality (or 'choice' as it is called in space syntax)

Closeness centrality captures the to-movement and the notion of accessibility of a location. It measures 'to what extent a node (segment) is close to all the other nodes along the shortest paths of the network' (see figures 3 and 5). (S. Porta et. al, 2009) The closeness centrality value for a particular node (street segment) can be mathematically defined as the inverse of the average distance from all other nodes (origins) to this given node (destination) along the shortest paths. The betweenness centrality captures the through-movement of each street segment. It does not capture the origin or destination for trips. A 'node is more central when it is traversed by a larger number of the shortest paths connecting all couples of nodes in the network'. (S. Porta et. al, 2009) The betweenness centrality for a particular node is calculated by counting how often this given node is traversed by all shortest paths (see figure 4). In chapter 1.3 you can find example calculations with the formulas and complementary visuals.

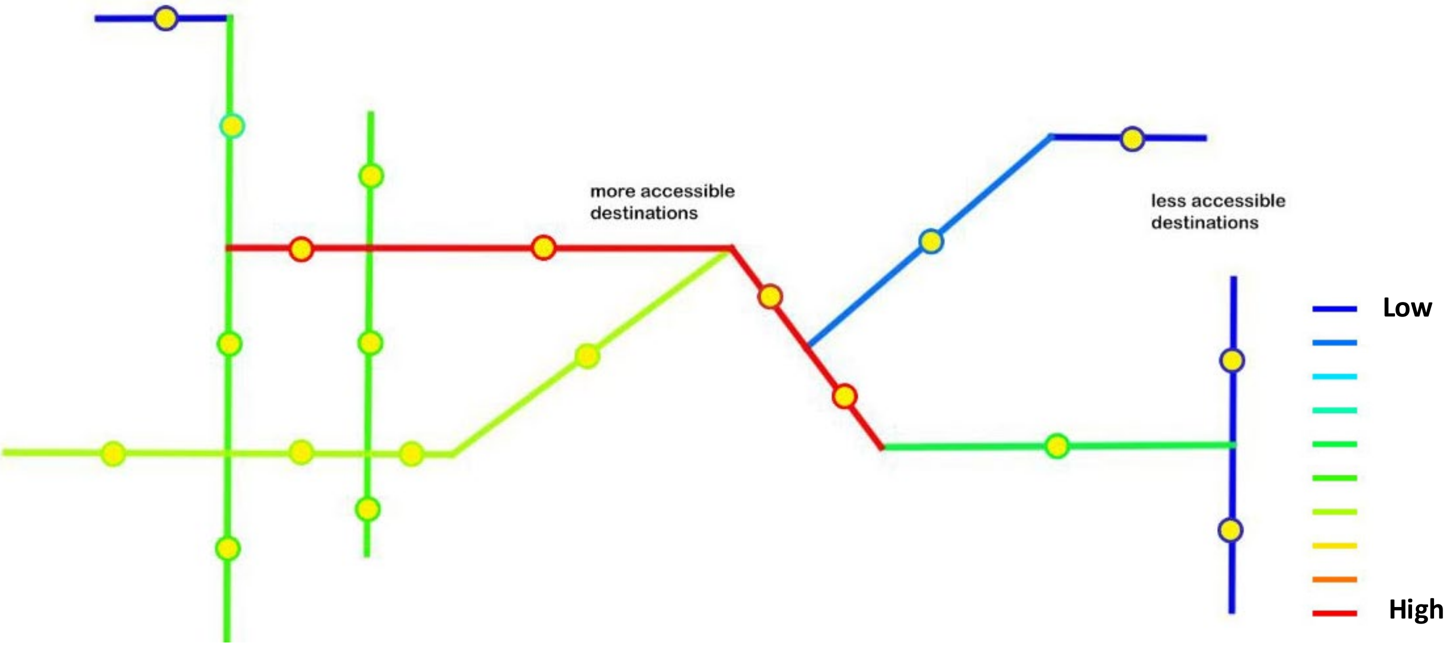


Figure 3, (Angular) Closeness Centrality Map Toy Street Network – To-Movement

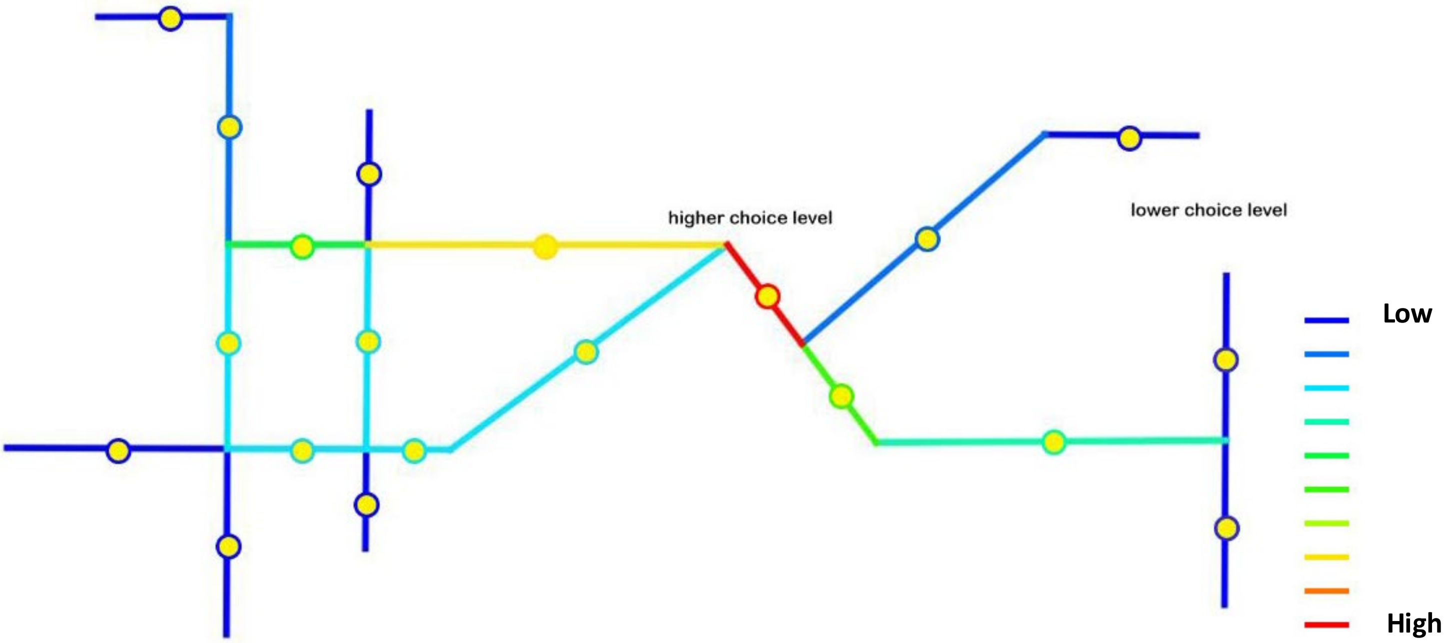


Figure 4, (Angular) Betweenness Centrality Map Toy Street Network – Through-Movement

For calculating the network centrality measures, the shortest paths need to be computed. The shortest path between an origin node and a destination node can be weighted by using three different definitions of distance; metric distance (see figure 6), topological distance (see figure 7) and angular distance (see figure 8). (B. Hillier & S. Lida, 2005) The shortest path shown in figure 5 happens to be the same for all three distance measures. This may not always be the case for other (more complex) spatial configurations. The urban space is regarded as a network based on 'human affordances of visibility and accessibility'. (Gibson, 1979, L. Marcus et. al, 2018) The topological and angular distance have the ability to capture human perceptions; 'how much can I see?'. The fewest turn path is based on the topological distance by counting each change of direction as one topological step even though the angle between 2 segments is close to 0 degrees (straight). In many Dutch cities the long main streets are curved. Using topological steps without angular weighting has a vast effect on the centrality values. (A. Van Nes, 2014) The Least Angle Change Path with angular distance is used as the default shortest path for this research (see spatial analysis methodology on page 26). The angular distance is an effective way of expressing the cost-benefit of choosing a particular path. The angular distance is quantified by dividing the angle change at each topological step by 90° (e.g. straight on are 0 steps, a 90° turn is 1 step and a U-turn are 2 steps). A route with many curves and turns at junctions will slow down the wayfinding through cities for pedestrians, cyclists and car drivers. (N. Dalton, 2001)

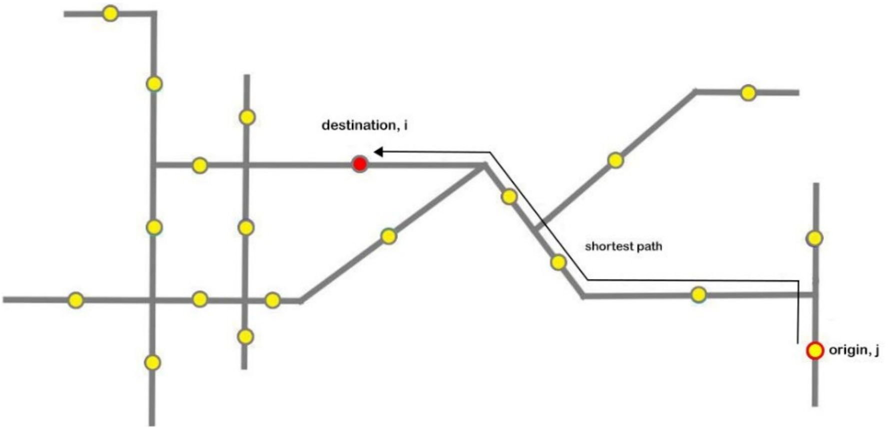


Figure 5, The shortest path from origin node (j) to destination node (i)

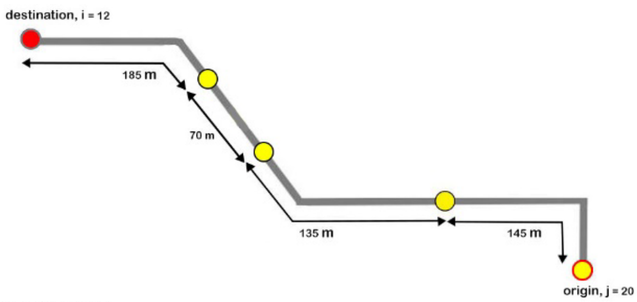


Figure 6, Least Length Path : metric distance, d_{ji} = 535 metres

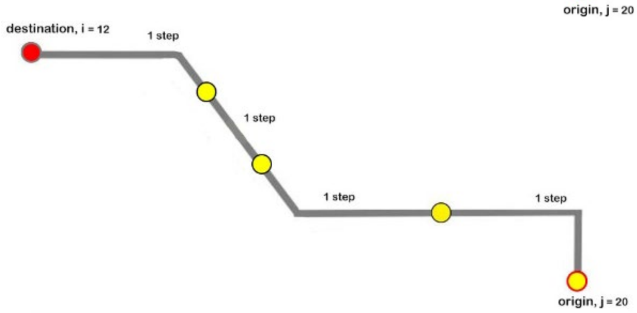


Figure 7, Fewest Turns Path: topological distance, d_{ji} = 4 topological steps

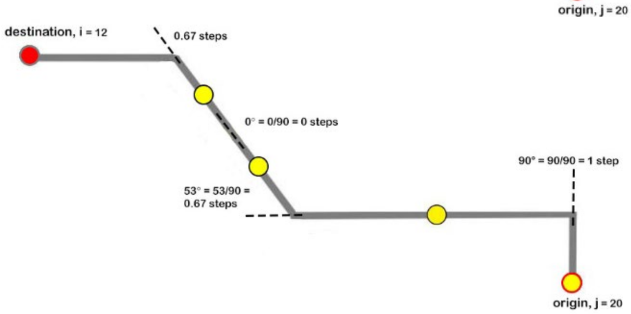


Figure 8, Least Angle Change Path: angular distance (weighted topological distance), d_{ji} = 196° = 196/90 = 2.18 topological steps

The closeness centrality and betweenness centrality measures can be performed on different spatial scales; the degree in which a node is integrated or segregated from a system as a whole (global) or as a partial (local). The maximum travelling (walking) distance from each node can be limited by applying a metric radius. Hereby you can test configurations that are ideal for different modes of transport using the road network. (See Appendix A1) Studies have shown that local scales (radius < 2500 m, see figure 9) are likely to highlight streets that are attractive for pedestrians and cyclists. Intermediate and global scales (radius > 2500 m, see figure 10) correspond better with the movement of motorized vehicles such as cars and buses. (B. Hillier et. al, 1998, A. Van Nes, 2005, D. Koch et. al, 2009) Some streets might just be local, others are local and global, and others are just global. Many cities consist of several centres whereas a global measure often only highlights one centre. By comparing local and global centrality maps you can observe how well local centres are integrated to the so called 'supergrid'. In other words; how well main routes connect neighbourhoods with each other. (A. Van Nes, 2014)

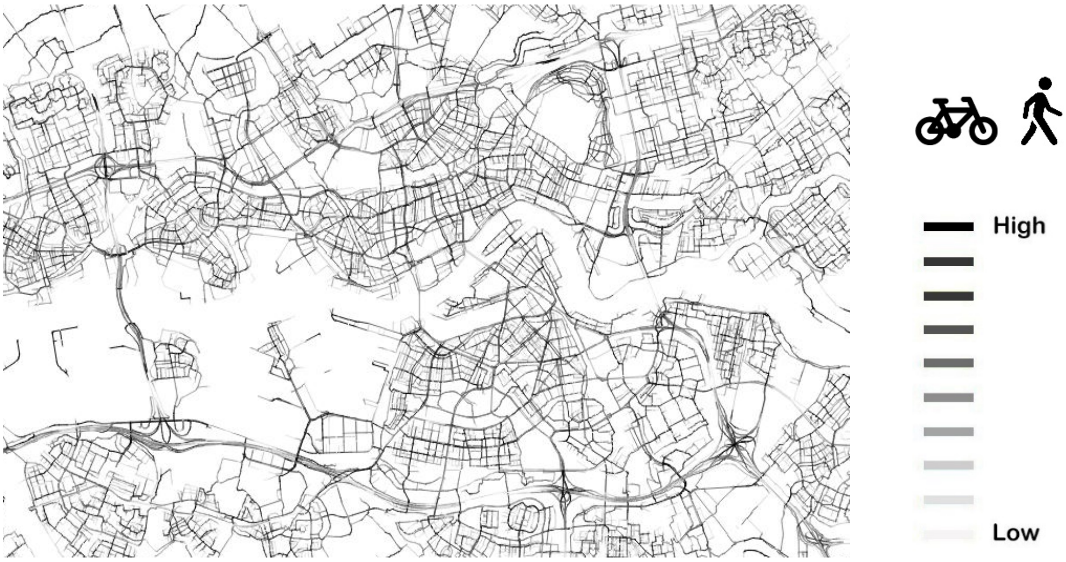


Figure 9, Local (Angular) Betweenness Centrality of Rotterdam (radius = 1000 m)

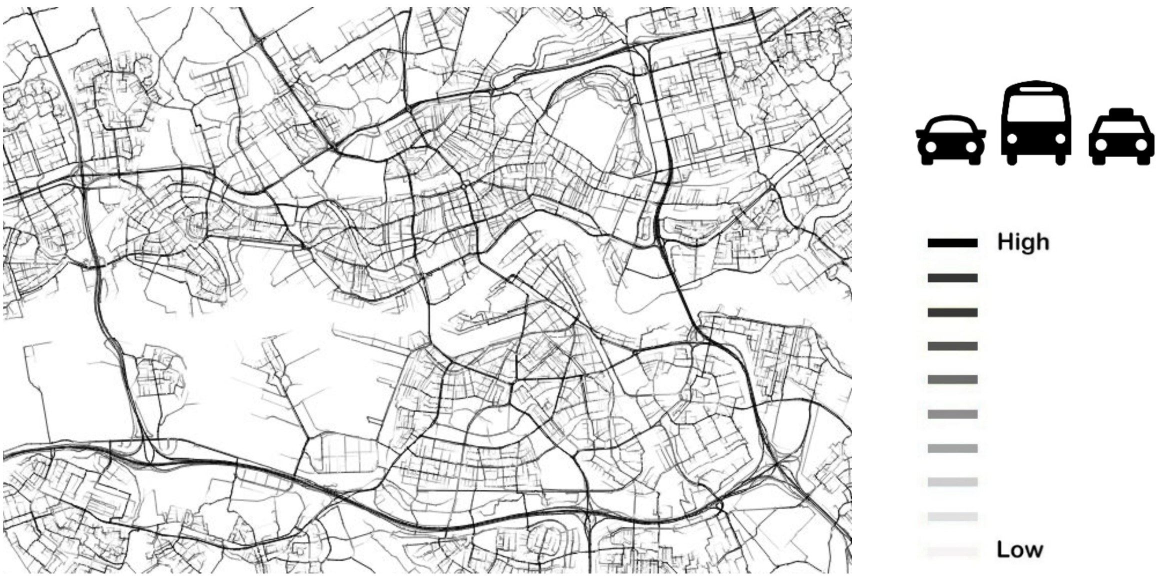


Figure 10, Global (Angular) Betweenness Centrality of Rotterdam (radius = 30 km)

The role of spatial configuration in the 'Circle of Wegener'

In order to understand how movement (vehicular movement in this particular case) is affected by the configuration of the street network, it is fundamental to be aware of how the different parts of the complex urban system are related to each other. The circle of Wegener (M. Wegener & F. Fürst, 1999) in figure 11 explains how the components of transport systems, accessibility, land-use and activities are related and form a 'dynamic' feedback cycle. This cycle is not completely closed due to influence of some other external factors as shown by L. Bertolini (2012) in the appendix A2.

The space syntax approach can indirectly capture the circle of Wegener by solely looking at the spatial lay-out of urban areas. (See figure 12) Studies by S. Porta (2009) confirm the hypothesis that street centrality has a crucial role in shaping the formation of urban structure and land uses. Network centrality measures can be used to predict social, cultural and economic processes of a location as centrality influences its attractiveness. For example, 'commercial activities seem to take place in the most globally integrated (most accessible) urban streets whereas dwelling areas are most located in segregated (less accessible) areas'. (B. Hillier, 1993, A. Van Nes, 2014)

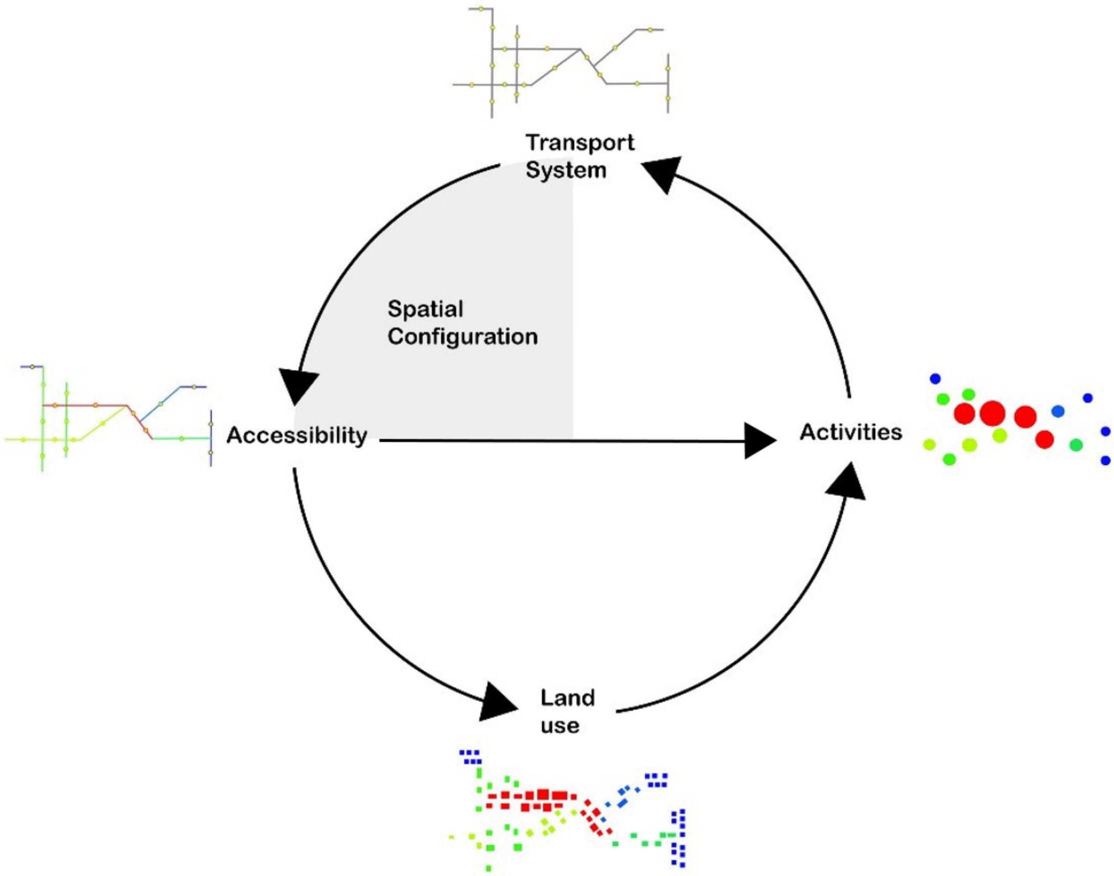


Figure 11, Simplified adapted Circle of Wegener (M. Wegener & F. Fürst, 1999) with effect of spatial configuration

The evolving space organization with physical and social boundaries and differentiation leads to a reciprocal relation between attraction and movement; so called the 'movement economy'. (Peponis, 2001) The urban structure determines the 'natural movement'; the proportion of movement that is determined by the urban fabric and not by 'special magnets' such as certain shops, services and activities. (B. Hillier, 2007) Central streets generate more 'natural movement' but the related functionality can lead to additional attraction and intensification of a certain distribution pattern; trip generations between origins and an attractive destination. When an originally less accessible location has 'special magnets' due to other external factors (see Appendix A2), the surrounding street network infrastructure will slowly be upgraded in order to improve its accessibility and thus generating more natural movement to attract more people.

For the scope of this research the transport system is limited to different transport modes using the road network by selecting ideal maximum travelling distances (spatial scale). The link loads and accessibility for a location can be captured by respectively betweenness centrality and closeness centrality (see figure 13). Both centrality measures are calculated by computing the route choices according to the shortest path from origin to destination. Accessibility has been previously defined as 'the amount and diversity of places that can be reached within a given travel time and/or cost' by L. Bertolini, F. le Clercq and L. Kapoen (2005). The closeness centrality measure with least-angle-change-paths reflects most accurately the 'spatial' accessibility; the travel cost of overcoming spatial separations between places with population and activities. The link loads (betweenness centrality) do not affect the captured accessibility (closeness centrality). However in practice it does; traffic congestions will influence the travel time and route choice. The computed shortest paths based on the spatial configuration do not take into account rerouting due to traffic flow intensity.

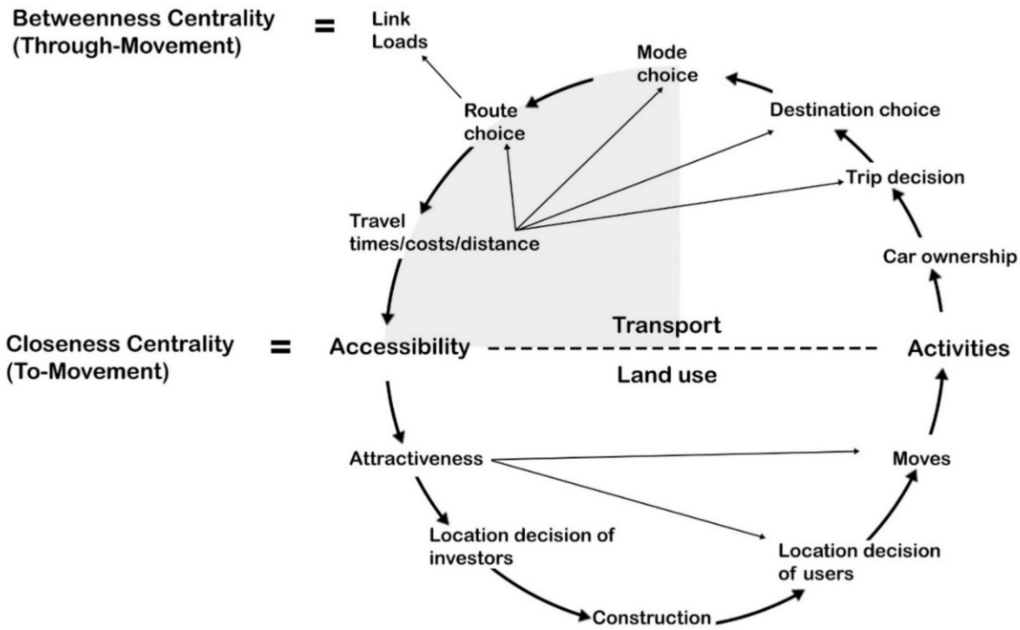


Figure 12, Detailed Circle of Wegener (M. Wegener & F. Fürst, 1999) with effect of spatial configuration

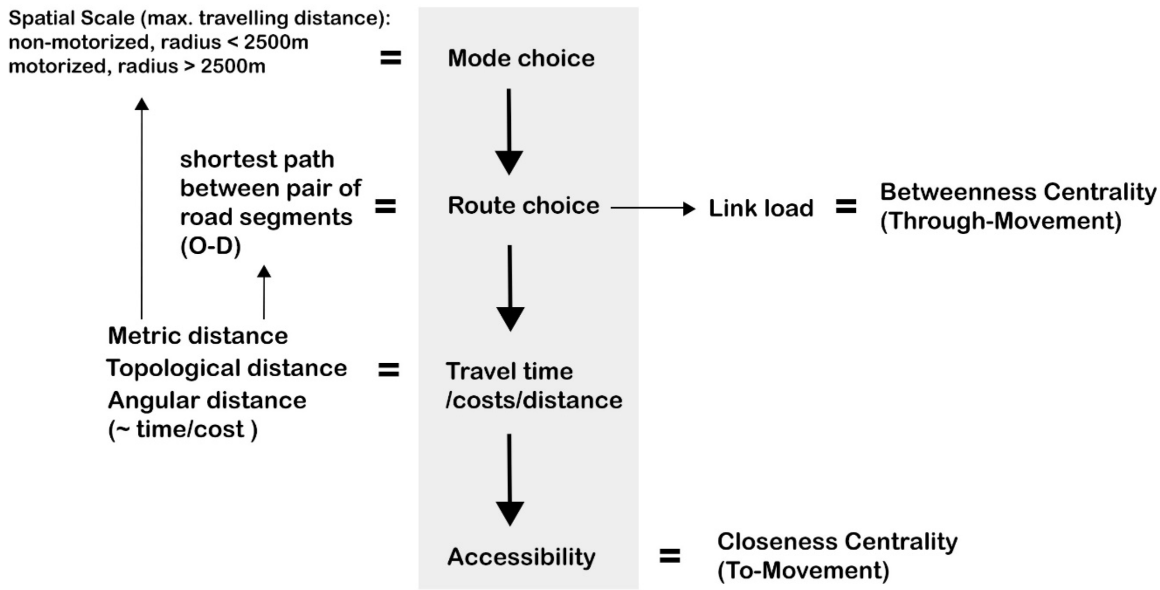


Figure 13, Relation between Network Centrality Measures and Circle of Wegener (M. Wegener & F. Fürst, 1999)

1.4 Network Centrality Measures on Toy Street Network

The toy street network is used again to explicitly demonstrate how the closeness centrality and betweenness centrality is calculated for a particular street segment (node). The total number of nodes (N) in the network is 20. Each node is given a unique reference number (see figure 14). For calculating the network centrality value of every single node in the network, the shortest paths between all possible combinations of segment pairs need to be computed beforehand.

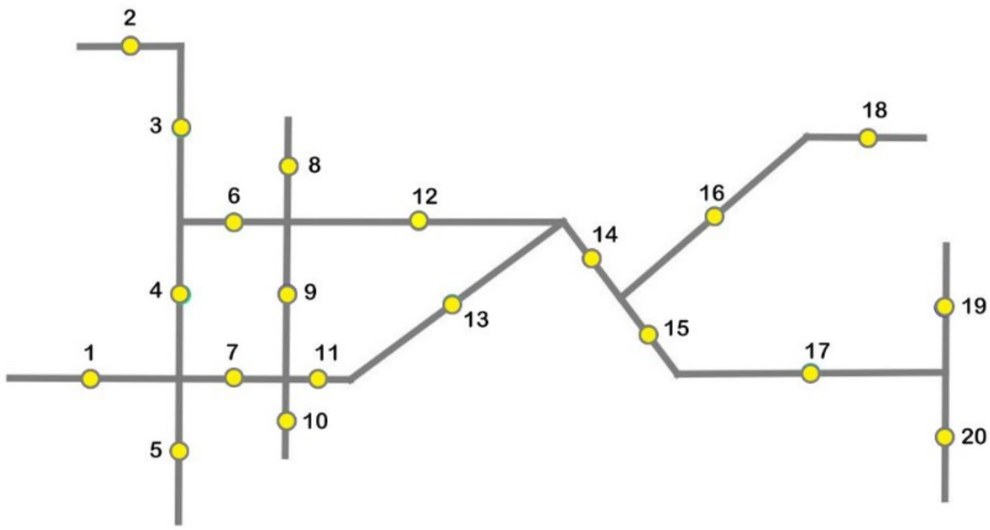


Figure 14, Graph notation of road centre line map toy street network with node reference numbers

The street segment with number 12 is selected as the destination node, for instance. The shortest paths can be computed with three different definitions of distance (see page 12). The least-angle-change-paths (angular) from all other nodes to node 12 is shown in figure 15 below. The Fewest Turns Paths (topological) and Least Length Paths (metric) can be found in the appendix A3.

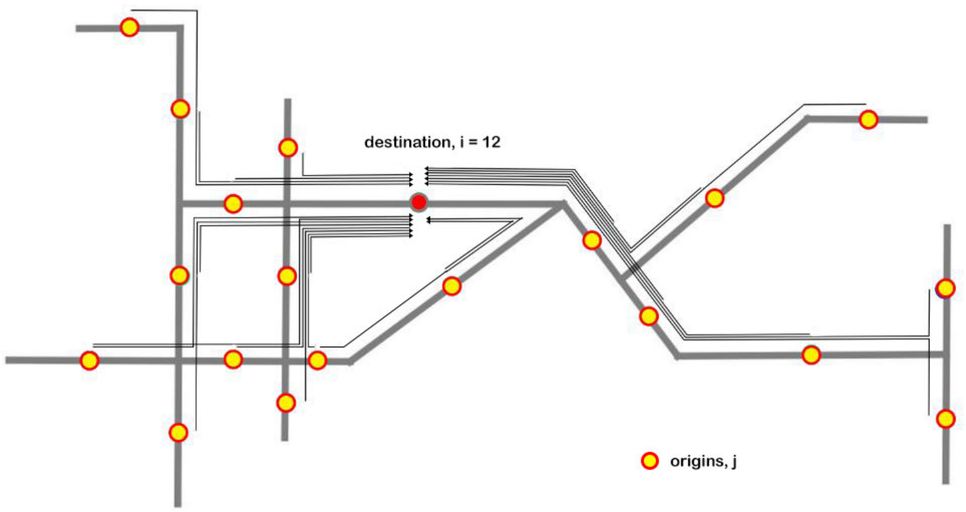


Figure 15, Least Angle Change Paths from origins (j) to destination node (i = 12)

Closeness Centrality

The closeness centrality value, C^c for a given node (destination) is calculated by the inverse of the average distance from all other nodes (origins) to this node. The distance (dij) between an origin node (j) and destination node (i) is also known as the step depth (D). The total distance and average distance from all origin nodes to a destination node are known as the total depth (TD) and the mean depth (MD). The derivation of the closeness centrality calculation is shown below. (S. Porta et. al, 2009)

$$C^c_i = \frac{N-1}{\sum_{j=1;j\neq i}^{N} dji} = \frac{N-1}{\sum_{j=1;j\neq i}^{N} Dji} = \frac{N-1}{\mathrm{TD}} = \frac{1}{\mathrm{MD}} \quad ,$$

Where N is the total number of nodes (segments) in the network and d_{ij} is the shortest distance between nodes j (origins) and i (destination).

The application of the inverse calculation is known as the 'method of relativization'. (B.Hillier & J. Hanson, 1984, Kruger, 1989) Relativization is also known as 'normalization'. Hence the angular closeness centrality is called Normalized Angular Integration (NAIN). The closeness centrality should be calculated for the entire network where each time another node is chosen as the destination node (i). The angular step depth from all origins to destination node 12 along the least-angle-change-paths are shown in figure 16 below. The metric and topological step depth values can also be found in the appendix A3.

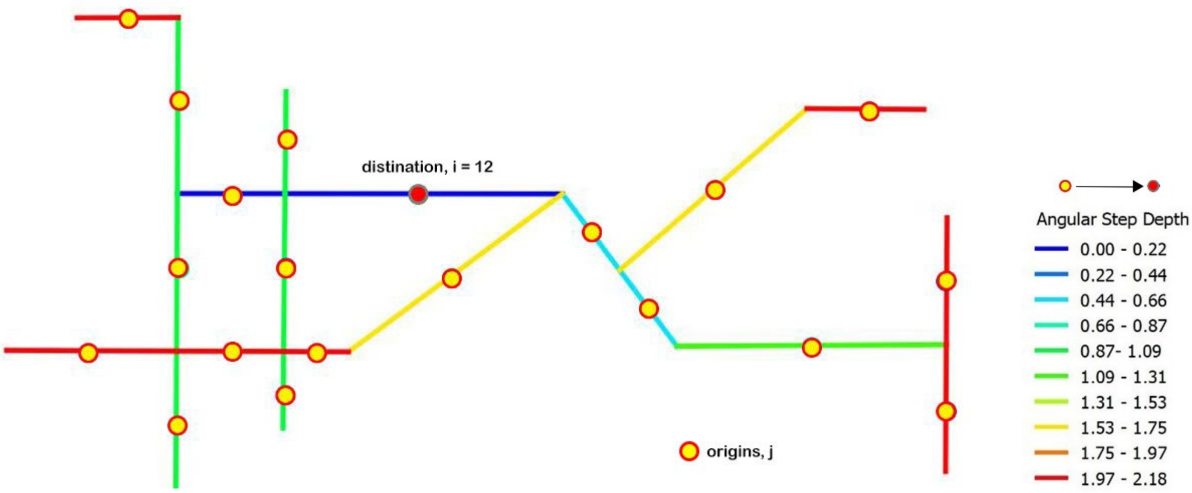


Figure 16, Angular Step Depth from origins (j) to destination (i = node 12)

The total angular step depth (TD) is expressed as the cumulative amount of angle change between all adjacent segments along the least-angle-change-paths. As previously explained on page 7 each change of direction is calculated as topological step with angular weighting. (N. Dalton, 2001) The angle deviation in degrees is divided by 90. This means that a straight line with 0 degrees gives 0 topological steps. An angle of 45 degrees costs 0.5 steps. An angle of 90 degrees costs 1 topological step and a U-turn of 180 degrees gives 2 topological steps. The weighting between these values varies depending on the number of bins; the angular precision used in the analysis. The number of bins used for this research is 1024. The angular closeness centrality for node 12 is given below.

$$AC^c_{12} = \frac{20-1}{\sum_{j=1;j\neq 12}^{20} d_{12j}} = \frac{20-1}{27.69} = \frac{1}{1.29} = 0.78$$

The angular closeness centrality map for the entire toy network can be found on page 6 and please refer to Appendix A3 for the metric and topological closeness centrality maps.

Betweenness Centrality

The betweenness centrality value, C^B for a given node is calculated by the number of shortest paths between all possible couples of other nodes that contain this node. The derivation of the betweenness centrality calculation is shown below. (S. Porta et. al, 2009)

$$C^B{}_k = \frac{1}{(N-1)(N-2)} \sum_{j=1;i=1;\ j \neq i \neq k}^{N} \frac{n\mathrm{ji(k)}}{n\mathrm{ji}} \quad ,$$

Where N is the total number of nodes in the network. $n$ji is the number of shortest paths between nodes j (origins) and i (destination) and $n$ji (k) is the number of these shortest paths that pass-through node k.

Unlike the closeness centrality calculation of node number 12, all shortest paths need to be known rather than only from the origins to one destination node. The betweenness centrality can also be measured with different means of distance. The angular betweenness centrality (AC) for node 12 is given below.

$$AC^B{}_{12} = \frac{1}{(20-1)(20-2)} \sum_{j=1;i=1;\ j \neq i \neq 12}^{20} \frac{n\mathrm{ji(12)}}{n\mathrm{ji}} \quad = 160$$

The angular betweenness centrality map for the entire toy network can be found on page 6 and please refer to Appendix A3 for the metric and topological betweenness centrality maps.

Normalized Betweenness Centrality

Normalizing the betweenness centrality is the potential solution to the paradox that complex segregated (low closeness centrality) grids add more total and average choice to the system than integrated (high closeness centrality) ones. Research by B. Hillier, T. Yang and A. Turner (2012) shows that segregated grids have fewer route choice (shortest path) options and were therefore predicting overall higher rates of movement than integrated grids. The normalized betweenness centrality is calculated by simply dividing the total betweenness by the total depth for each segment in the system. The more segregated street segments will have a more reduced choice value. The derivation of the angular betweenness centrality (or 'Normalized Least Angle Choice' (NACH) as it is called in space syntax) calculation is shown below. (Systematica, 2018)

$$\mathrm{NACH_k} = \frac{\log(\sum_{i=1}^{N} \sum_{j=1}^{N} \sigma(i,k,j)+1)}{\log(\sum_{i=1}^{N} \mathrm{d\theta}(i,k)+3)} \quad (\mathrm{i} \neq k \neq j),$$

Where N is the total number of nodes (segments) in the network and (i, k, ,j) = 1 if the shortest path from i to j passes through node k and 0 otherwise.

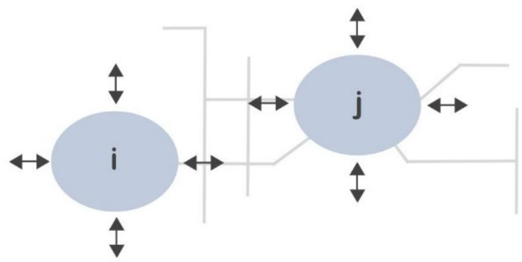
1.5 Space Syntax vs Four Step Macroscopic Traffic Model

For the scope of this research the network centrality measures of the urban area of the city Rotterdam are compared to the predicted traffic loads from a traditional four-step macroscopic model (see chapter 4 for results). These predicted traffic loads are the benchmark as there is insufficient observed traffic count data available to do a comprehensive validation. Before comparing numerical values it is evident to distinguish the principal differences between the two modelling approaches. This chapter is a systematical comparison between both approaches.

Four-Step Macroscopic Traffic Model

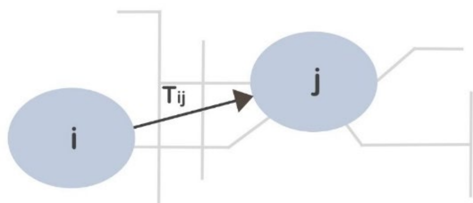
A four-step macroscopic model is an instrument to support decisions when planning and designing transportation systems. It can be applied for different scales such as urban, regional but also long distance forecasting and assignments. (Systematica, 2018) The traditional traffic model is mainly constituted by trip generation and trip assignment between discrete areas; origins (i) and destinations (j). The four steps in macroscopic traffic modelling can be defined as the following (A. van Werken, 2018):

1. Trip generation



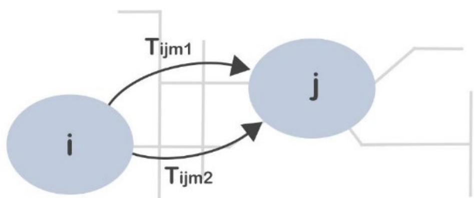
Origin (i) – destination (j) matrices are determined for different travelling motives within given time periods (morning peak, evening peak and rest of the day) with all required socio-economic and demographic input data (Land-use, Population, Jobs, Students, etc.). The matrices contain the amount of production and attraction of passengers (sums of matrix rows and columns). There is no distinction made between mode choices yet.

2. Distribution



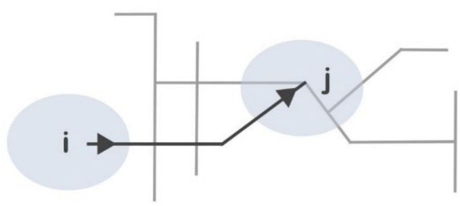
The distribution model completes the matrices by quantifying the number of trips (T_{ij}) between a particular origin (departments) and destination (arrivals). It works as a gravity model; the greater the resistance between two points, the smaller the number of displacements between these points. The resistance or quality of accessibility are dependent on the travelling time (cost per motive), distance (different costs per travelling mode), optional penalty costs (parking or interchange costs) and travel behavior.

3. Mode choice



The mode choice model splits the travel choices. It divides the total displacement by different travelling modes such as private car (T_{ijm1}), Public Transport (T_{ijm2}), cycling and walking.

4. Trip Assignment



The last step, trip assignment predicts the actual route taken given an origin, destination and a mode of transport. By computing all possible trip assignments for a given time period (e.g. morning peak) it is then possible to calculate the link loads; the number of passengers or vehicles passing through each street segment. When the link loads exceed the road capacity the traffic flow decreases. Congestion and slower driving speed increases the resistance of moving between areas and choosing a particular route. Feedback and multiple iterations are included to the distribution model (step 2) to re-distribute the number of trips.

Figures 17, 18, 19 and 20 (From top to bottom), Principle diagrams of Four Step Macroscopic Traffic Model

Space Syntax and Weighting Functions

As previously mentioned in the theoretical framework the space syntax approach is based on two central variables; distance and attraction. The closeness and betweenness centrality measures show respectively the potential to-movement and through-movement of each street segment in the road network. The total movement can also be interpreted as the sum of to-movement and through-movement. The 'links' known in a macroscopic traffic model are not aggregated in zones (to limit dataset) but all trips are illustrated on an axial or a segment map. An axial line is defined as 'the longest straight line representing the maximum extension of a point of space'. A segment map is constructed from an axial map by breaking its lines at the intersections. A. Turner (2007) confirms that road-centre line maps can produce comparable correlation results for vehicular flow as segment map (given that road centre lines are also broken at intersections). Both centrality measures are simply a function of the defined distances and shortest paths between segment pairs (nodes). There is no input variable of production of a location. Higher street centrality suggests greater attractiveness for intensive land-use and more activities and movement. In practice, this may not always be a one-on-one relationship.

Weighting functions can be applied as specific location-based qualities and road characteristics (see figure 21) of the network infrastructure may influence movement patterns for a given scale/travelling distance. In other words the street segments are given additional attractiveness; some network centrality values become relatively larger while others are decreased. Without weighting functions all street segments are treated equally. With the recently developed Place Syntax Tool (A. Ståhle, 2012) for QGIS (Geographic Information System Software), the betweenness and closeness centrality measures can be combined with geographic accessibility data. Aggregated location-based density and differentiation (e.g. population density, building floor space index and functions) can be assigned as a weighting to their nearest located street segments.

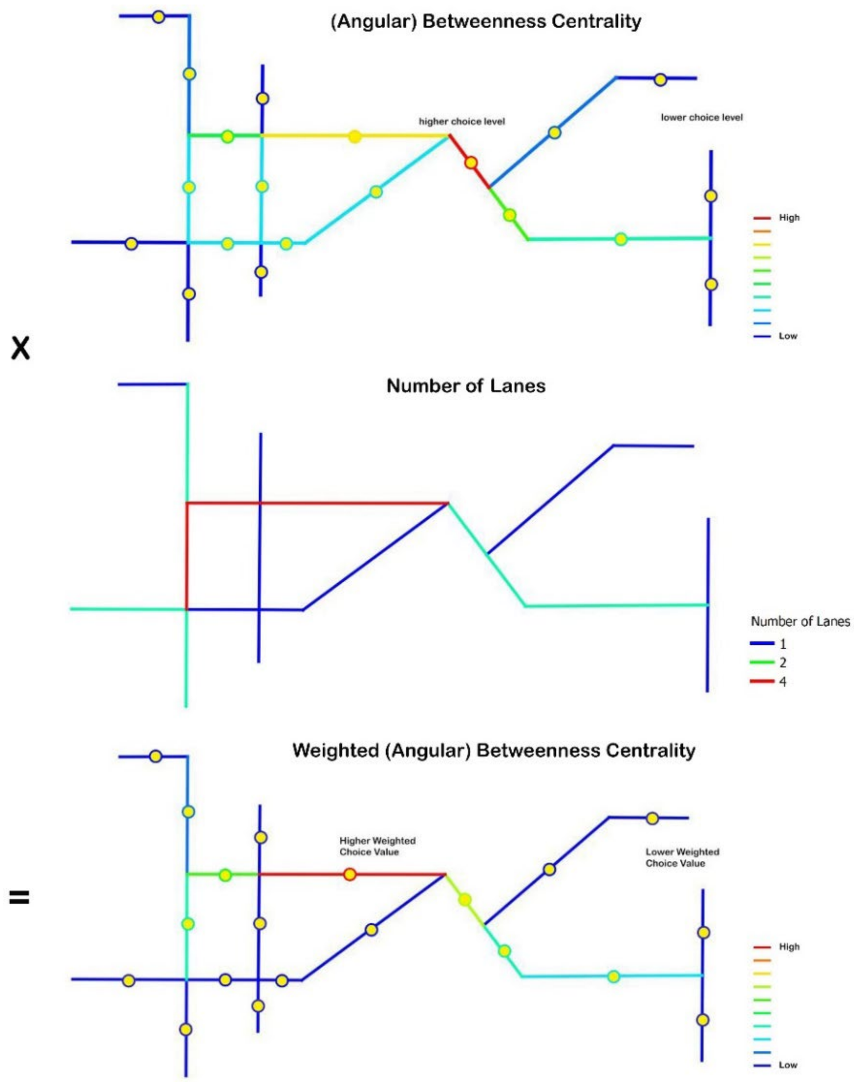


Figure 21, Weighted (Angular) Betweenness Centrality map by the number of lanes per street segment

Space Syntax Limitations

The application of space syntax for vehicular movement prediction still has many limitations to be addressed. The network centrality measures are based on a static network with no dynamic or time dimensions. Time dependent and dynamic weighting functions should be added but this would require a lot more data management and availability. Although the more required data collection, the closer it will become to an alternative macroscopic traffic model. Before analysing the movement pattern of one particular mode choice (e.g. vehicular movement), non-accessible roads in the network need to be erased. Some road centre line map data contain all road categories; motorized, non-motorized and shared roads. Junctions, tunnels and fly-overs between intersecting street segments need be indicated if not already considered by the road centre line data source. This can be manually done by joining or breaking the lines. At the moment, there is also no solution for one-way traffic streets. All these infrastructural characteristics are necessary to be incorporated in the space syntax model as they will influence the computation of the desired shortest paths (route choice).

Data Collection and Processing Comparison

A simpler modelling technique and data collection makes it more likely that the model will be used in practice and will be transferable to other disciplines such as urban planning and environmental policy-making. It keeps the model as well as the results very transparent, since everyone can follow the result production. The data collection and the processing time can vary according to the study area and availability of resources. For exact comparison between space syntax (see figure 23) and a four step macroscopic traffic model (see figure 24), big data performance models can be used to see how much input data each method requires to produce accurate and reliable output data.

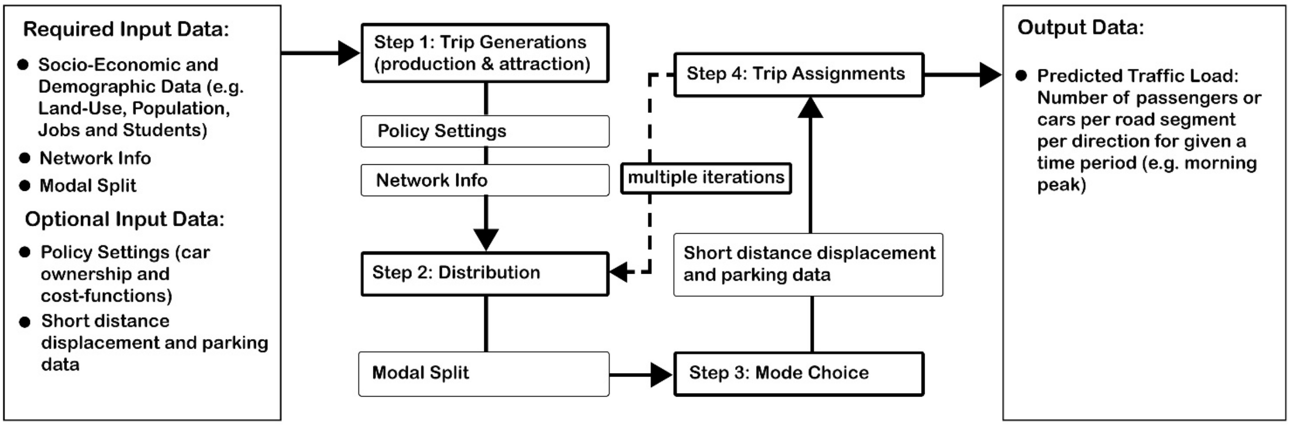


Figure 22, Four Step Macroscopic Traffic Model Data and Approach

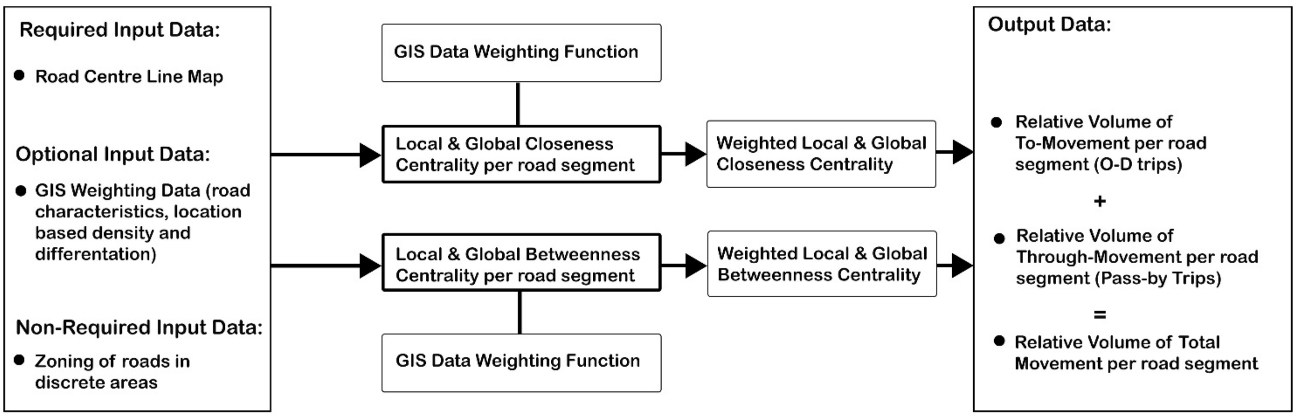


Figure 23, Space Syntax Data and Approach

2. Methodology

The research of this report consists of an analytical comparison between unweighted and weighted network centrality measures from the space syntax approach, and the predicted traffic loads from a four step macroscopic traffic model for the city of Rotterdam. The methodology in this chapter describes the approach and the required steps (see appendix A10 for manual steps). The methodology can be subdivided by the following three stages:

1. **Study area and data preparation**
2. **Spatial Analysis**
3. **Statistical Analysis**

1. Study area and data preparation

Study area

The study area is the urban area of the city of Rotterdam (red boundary zone). Rotterdam is located in the western part of The Netherlands in the province of South-Holland (blue boundary zone) (see figures 24, 25 and 26). The domain of the urban area of Rotterdam is selected by aggregating the urban districts from the zonation in QGIS (geographic information system software). The study area covers 325.8 km² and has an estimated population size of 638,712 (CBS StatLine, 2018). The study area does not include the western harbour front which is also part of the administrative municipal area of Rotterdam. Nearby cities in South-Holland include Delft, Leiden and The Hague.

Figure 24, 25 and 26 (Left to Right), Geographic maps of location study area within The Netherlands and South-Holland (Open Street Map Data, 2019)

The city of Rotterdam has a very dynamic character. The infrastructure and economy have been constantly changing throughout time. The river Maas divides the North and South of Rotterdam and plays a crucial role in shaping the city's growth. (See figure 26) Each new tunnel or bridge across the river is a huge step forward in uniting the city's social, cultural and economic processes. The 'wederopbouw' (reconstruction) of Rotterdam after the Second World War bombing in May 1940 has left an evident mark on the city's urban structure. Historically the waterfronts in the study area used to be identified by intensive harbour industry. However since the 1950's the harbour has gradually shifted to the western front. The previously occupied harbour basins and neighbourhoods are nowadays subject to redevelopment with new housing and job opportunities. The road network and public transport network form together the backbone of the city, on top of the original polder and harbour landscape. It is therefore essential that the alterations and expansion of the spatial lay-out are carefully considered.

The research involves a considerable amount of data management. The required data management can be categorized by the extracting and modifying of the road centre line map data and the macroscopic traffic model dataset, and matching the street segments from both datasets for the statistical analysis.

Spatial analysis dataset

Prior to the spatial analysis of the study area's street network, the road centre line map data needs be extracted and modified. (See Appendix A5 for detailed steps) It is important that the lines are broken at the junctions to capture the change of direction between consecutive street segments. In this research the dutch 'Nationaal Wegenbestand' (NWB) from 2018 is used as the import data. The road centre lines are selected by location using a buffer area of 30 km from the boundary edges of the study area. (See figure 27) This makes it possible to use spatial scales up to 30 km for the network centrality measures. By knowing the size of the study area we know what exact metric radii we have to apply to avoid edge effects; 'the distortion that lowers network centrality values near the edge of a network'. (A. Turner, 2007) These distortions have a considerable effect for centrality measures on highly fragmented networks. The total number of individual street segments in dataset is 415,041 (see figure 28).

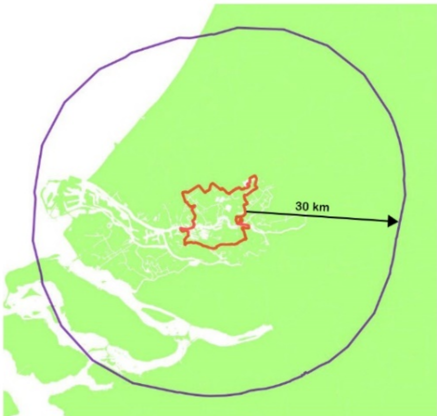


Figure 27 and 28 (Left to Right), 30 km buffer zone from (red) boundary edges of study area

Macroscopic traffic model dataset

The four-step macroscopic traffic model that is used for the purpose of this research is the V-MRDH 2.0 omniTRANS model made by Goudappel Coffeng. The permission has been granted by the V-MRDH traffic model administrator from the Metroolpoolregio Rotterdam Den Haag (MRDH) in April 2019. The extracted data is from 2016 and includes the predicted average hourly motorized traffic load specified in number of vehicles per hour and road attributes such as the capacity and driving speed per direction (see figure 31) for the given link numbers. These road attributes are used as weighting functions. The network centrality measures cannot capture movement per driving direction, therefore the sum of both driving directions for total predicted traffic load (see figure 29) and road capacity (figure 30) is used. (E.g. Total Link Load = LoadAB + LoadBA)

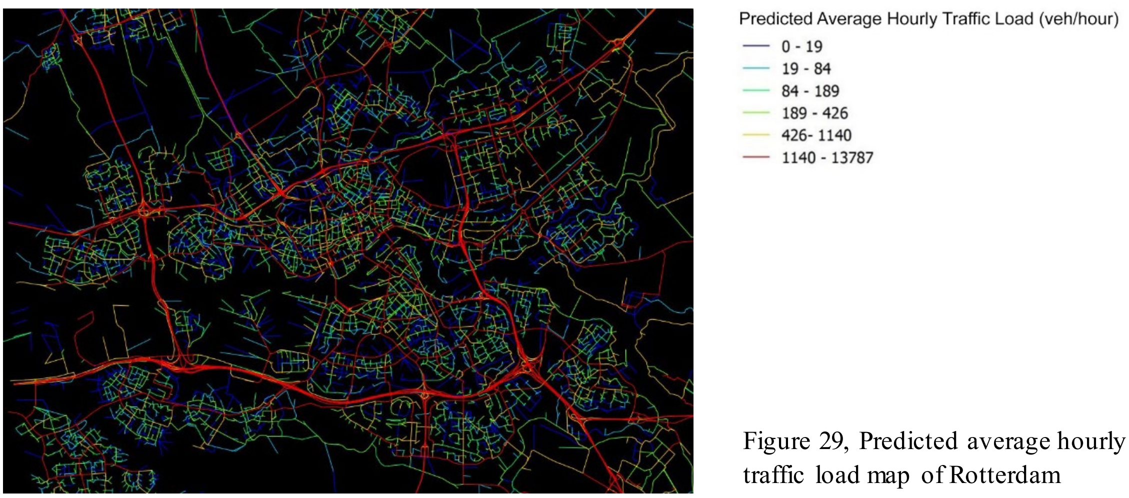


Figure 29, Predicted average hourly traffic load map of Rotterdam

Figure 30, Road capacity map of Rotterdam

Figure 31, Speed Limit map of Rotterdam

Matching street segments from both datasets

The individual street segments from both datasets need to be matched at the same geographic location/coordinates. The macroscopic model does not contain all streets and some links used in the macroscopic traffic model are not as accurately located as in the road centre line map. Therefore, only matching data is compared to each other. The road centre lines are selected that lie within a 5 m buffer from the macroscopic model links by using a spatial query in QGIS (see figure 32). The number of matching street segments selected in the study area is 17124.

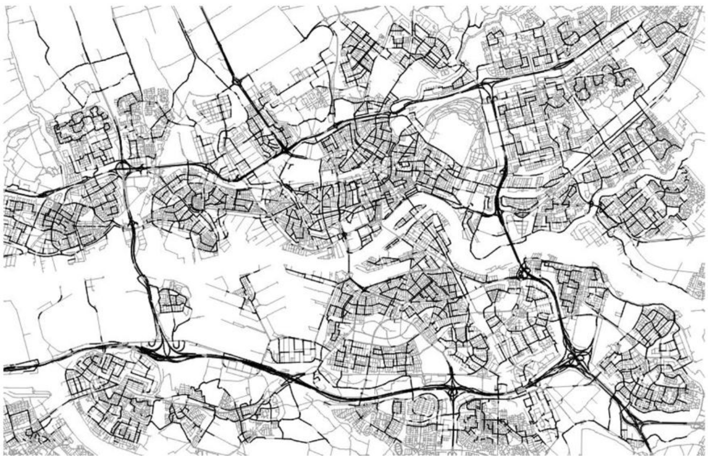


Figure 32, Matching road segments study area

2. Spatial Analysis

The road centre line map of the study area undergoes a spatial analysis with local, intermediate and global scales. (See page 8 about spatial scales) The applied metric radii are 1km, 2.5km, 5km, 7.5km, 10km, 15km, 20km to 30km (equivalent to global scale due to selected buffer area). The shortest paths will be weighted by the least angle change. Previous measures from angular segment analysis algorithms have proven to produce the best correlations with observed pedestrian and vehicular movement. (B. Hillier & S. Lida, 2005, T. Yang et. al, 2012) The spatial analysis measures consist of the angular closeness centrality (or normalized angular integration (NAIN) as known in space syntax), angular betweenness centrality (or angular choice (AC)) and normalized angular betweenness (or normalized angular choice (NACH)). The spatial analysis is run by the Place Syntax Tool Plug-In on QGIS software. The results of the spatial analysis can be found in chapter 3 of the report.

3. Statistical Analysis

In the statistical analysis the unweighted and weighted network centrality measures with various spatial scales are compared with the predicted traffic loads from the macroscopic traffic model. The network centrality measures of each street segment are weighted by being multiplied with its corresponding road characteristics; segment length, speed limit and road capacity. A simple linear regression analysis is used to evaluate the linear relationship between two variables. The independent variables (X) are the unweighted and weighted centrality measures. The dependent variable (Y) is the predicted hourly (day average) traffic load by the macroscopic traffic model (veh/hour). The sum of both network centrality measures is also used to validate the hypothesis that the total movement can be defined by combined efforts of to-movement and through-movement. The output values are the Pearson correlation coefficient, r and the coefficient of determination, R^2. The results of the statistical analysis can be found in chapter 4 of the report.

The Pearson correlation coefficient, r measures the measure the strength and direction of the linear correlation between two variables X and Y. The formula and interpretation of r (table 1) are given below where N are the number of observations.

$$r = \frac{N(\Sigma XiYi) - (\Sigma Xi)(\Sigma Yi)}{\sqrt{[N\Sigma Xi^2 - (\Sigma Xi)^2][N\Sigma Yi^2 - (\Sigma Yi)^2]}}$$

Pearson correlation coefficient, r	**Level of linear dependence of X & Y**
0 - 0.3	Weak positive
0.3 – 0.7	Moderate positive
0.7 – 1.0	Strong positive

Table 1, Interpretation of Pearson correlation coefficient, r

The coefficient of determination, R^2 is the proportion of the variance in the dependent variable that is predictable from the independent variable(s). The formula of R^2 is simply the squared value of the Pearson correlation coefficient, r and can't be negative. The interpretation of R^2 is given in table 2 below.

$$R^2 = r^2$$

Coefficient of determination, R^2	**Level of predictability of Y**
0	Y cannot be predicted by X
E.g. 0.2	E.g. 20 % of Y is predictable by X
> 0.7	Statistically significant
1.0	Y can be predicted by X without error

Table 2, Interpretation of coefficient of determination, R^2

3. Spatial Analysis

This chapter demonstrates the unweighted network centrality measures of the study area with one local (radius = 1 km) and one global spatial scale (radius = 30 km). The measures are presented on maps with classic graduated space syntax colour coding. The centrality maps of the other spatial scales can be found in the appendix A6. The colour classes are based quantile ranges (equal count) of the centrality values. The analysis of the network centrality maps make it possible to visually identify which streets in Rotterdam are more likely to generate movement within the given radius. The red colour indicate the highest network centrality and thus more relative to-movement or/and through-movement. The blue colour indicates less movement. The theory and derivation of the measures can be found in the chapters 1.2 and 1.3.

3.1 Closeness Centrality Measures

The local angular closeness centrality map in figure 34 below illustrates the streets that are most accessible for a maximum travelling distance of 1000 metres. The spatial scale is ideal to identify urban pedestrian movement patterns. Certain ring road segments are also shown in red, especially the interchanges although they cannot be accessed by pedestrians and cyclists. The map also highlights multiple local centres (neighbourhoods in both north and south of Rotterdam). These central streets are more likely to have clusters of commercial activities and retail services within walkable reach.

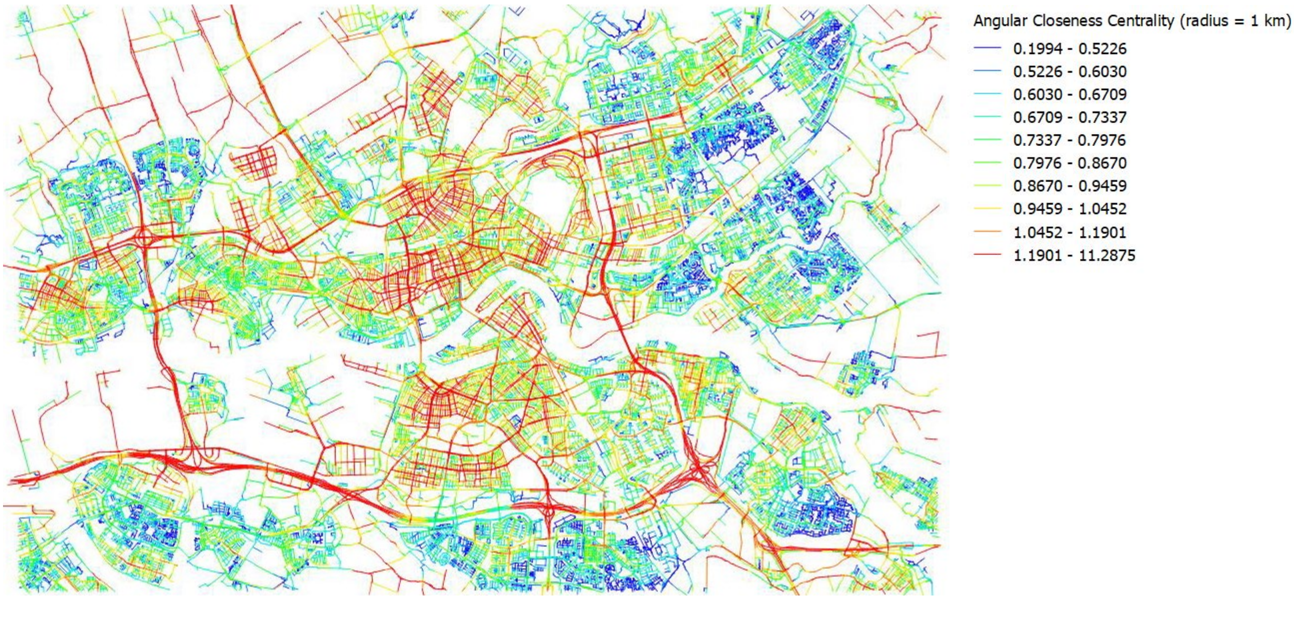


Figure 33, Local Angular Closeness Centrality (radius = 1000 m)

The global angular closeness centrality map in figure 34 on the following page shows the streets in the study area that are in closest proximity to (nearly) all other segments in the entire street network dataset (see figure 28). This global measure incorporates large distance displacements up to 30 km. These distances are typically covered by motorized vehicles. The ring roads are the most centrally located (red). The yellow and orange coloured streets show the urban roads that are most integrated for car drivers. Therefore (visitor) car parking may also be located along these streets in vicinity of the local centres (figure 33). The darker (blue) colours indicate the globally segregated streets and thus more likely to be related with residential land-use or harbour industry that is connected to another transport network such as the waterway.

Figure 34, Global Angular Closeness Centrality (radius = 30 km) map

3.2 Betweenness Centrality Measures

The local angular betweenness centrality map in figure 35 shows which street segments are potentially used for pass-through movement in walkable trips (1 km) between their origin (e.g. home) to their local destination (e.g. local supermarket). These in-between routes are frequently related to retail activities such as bars and restaurants. They are often located on the (urban) routes that are traversed by many pedestrians and cyclists.

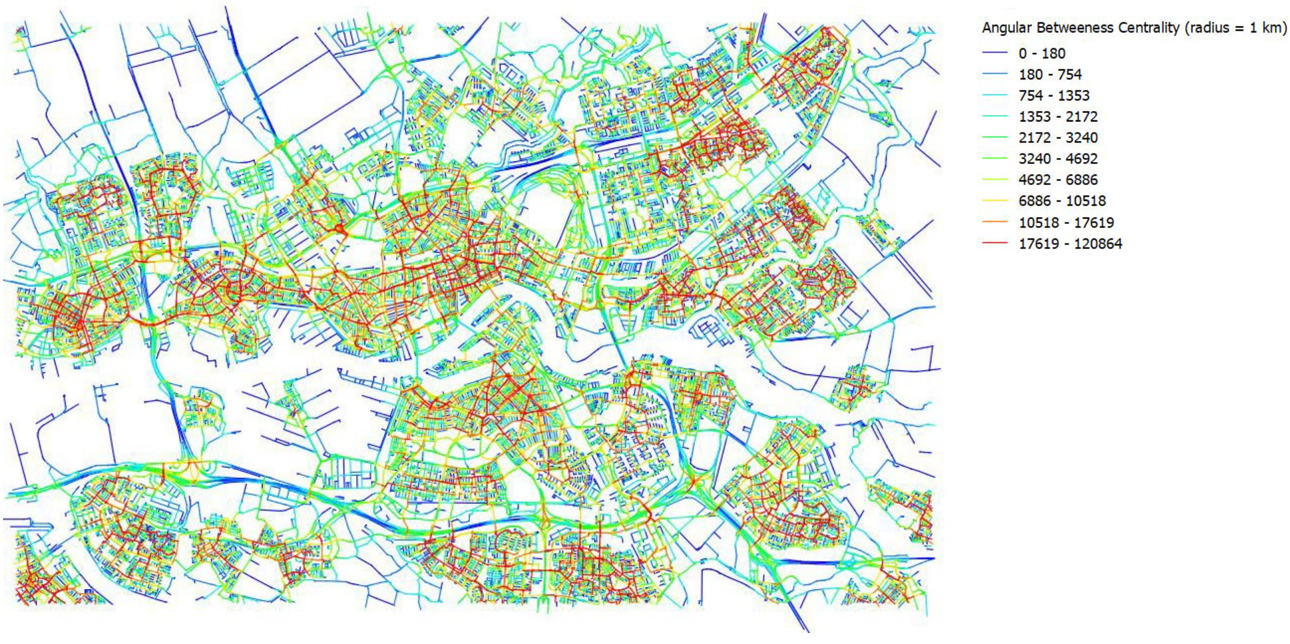


Figure 35, Local Angular Betweenness Centrality (radius = 1000 m) map

The global angular betweenness centrality map in figure 36 shows the streets that attract the most through-movement for all possible displacements between origins and destinations within a 30 km radius. Unlike all previous network centrality maps, the global betweenness centrality map demonstrates an evident (global) structure and spatial hierarchy of the city's street network. The ring road and arterial roads are clearly visible in red. These main urban routes have potential to be vital city boulevards when they are well integrated with local centres and routes. If not, these routes may contribute to spatial and socio-economic segregation between neighbourhoods. Spatial segregation in urban areas are often associated with higher crime rates and poverty. (H. Andersen, 2002)

Figure 36, Global Angular Betweenness Centrality (radius = 30 km) map

3.3 Normalized Betweenness Centrality Measures

The normalized angular betweenness centrality maps in figures 37 and 38 are similar to the angular betweenness centrality maps however, the betweenness centrality values of the more segregated streets (lower closeness centrality) are lowered compared to the more integrated streets (higher closeness centrality). The largest relative changes are most visible in the local scale centrality maps consists of multiple small spatial grids/centers. The normalization of the betweenness centrality values makes it possible to combine with the closeness centrality values (see figure 40).

Figure 37, Local Normalized Angular Betweenness Centrality (radius = 1000 m) map

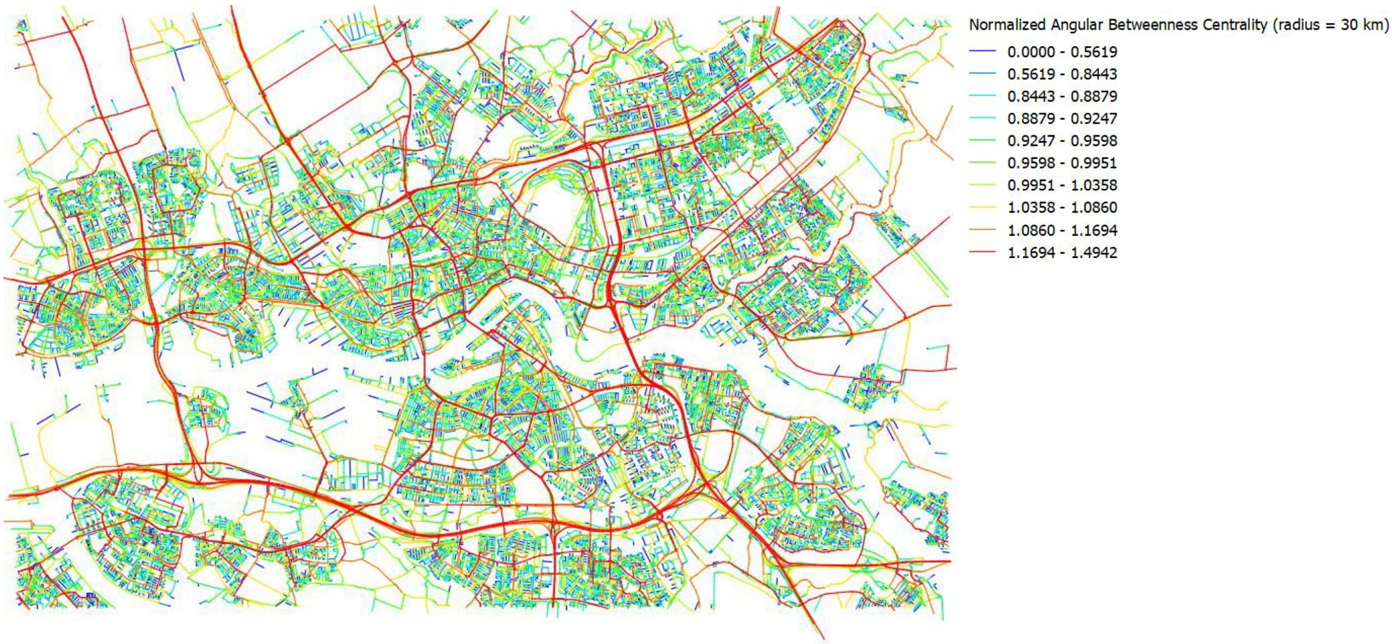


Figure 38, Global Normalized Angular Betweenness Centrality (radius = 30 km) map

4. Statistical Analysis

In this chapter the simple linear regression analysis is performed twice for the set of matching street segments: in the unweighted and the weighted case to measure the impact of the weights by road characteristics. The results are presented in tables with the Pearson correlation coefficient, r and coefficient of determination, R^2. The independent variables (X) are the unweighted and weighted centrality measures at various spatial scales. The dependent variable (Y) is the predicted hourly traffic load by the macroscopic traffic model (vehicles/hour). The statistical dataset consists of 17124 matching street segments (observations). The scatterplots between the two variables show all individual observations.

4.1 Unweighted Simple Linear Regression Analysis

The results from the simple linear regression analysis for the unweighted network centralities at different spatial scales are shown in table 3 below. Without weighting functions all street segments are treated equally. The scatterplots with the most correlating individual network centrality measures can be found in the appendix A7.

Spatial Scale (max. travelling distance)	Angular Betweenness Centrality (AC)		Normalized Angular Betweenness Centrality (NACH)		Angular Closeness Centrality (NAIN)	
Radius (m)	**r**	**R^2**	**r**	**R^2**	**r**	**R^2**
1000	-0.19	0.04	-0.15	0.02	0.34	0.12
2500	-0.06	0.00	0.00	0.00	0.39	0.15
5000	0.18	0.03	0.21	0.05	0.47	0.22
7500	0.34	0.11	0.23	0.12	0.56	0.31
10000	0.45	0.21	0.04	0.16	0.59	0.35
15000	0.59	0.35	0.47	0.23	0.60	0.35
20000	0.63	0.39	0.51	0.26	0.61	0.37
30000	0.61	0.38	0.53	0.28	0.60	0.36

Table 3, r and R^2 values with unweighted Angular Network Centrality measures

The resulting correlation coefficients show a reasonable positive linear relationship between the individual angular betweenness centrality and angular closeness centrality measures, and the predicted traffic loads from the V-MRDH OmniTRANS traffic model. The network centrality measures with spatial scales with radii ranging between 15 km and 30 km (global scale) provide the highest correlation coefficients. The unweighted angular betweenness with radius 20 km gives an r coefficient of 0.63. This can be logically explained as the average daily travelling distance by car in The Netherlands for 2017 was 29.11 km. (CBS StatLine, 2017) The average displacement distance in Rotterdam is expected to be lower due to its extensive public transport network and cycling infrastructure.

Combined Angular Closeness Centrality and Normalized Angular Betweenness Centrality

According the hypothesis mentioned in the introduction, the sum of the closeness centrality and betweenness centrality captures the total movement by combining the relative through-movement and to-movement. The network centrality measures with radii 20 km and 30 km are re-used and shown in table 4 below as they produce the highest r and R^2 values.

Normalized Angular Betweenness (NACH) + Angular Closeness Centrality (NAIN)	**r**	**R^2**
NACH (radius = 20 km) + NAIN (radius = 20 km)	0.66	0.44
NACH (radius = 30 km) + NAIN (radius = 30 km)	0.65	0.43
NACH (radius = 20 km) + NAIN (radius = 30 km)	0.65	0.41
NACH (radius = 30 km) + NAIN (radius = 20 km)	0.67	0.44

Table 4, r and R^2 values with combined Angular Closeness and Normalized Betweenness Centrality measures

The sum of the unweighted angular closeness and the normalized angular betweenness with radii 20 km and 30 km give the highest correlation coefficient as well as the highest coefficient of determination. The individual independent and dependent variable observations are shown in the scatterplot in figure 39. The red line is the line of best fit.

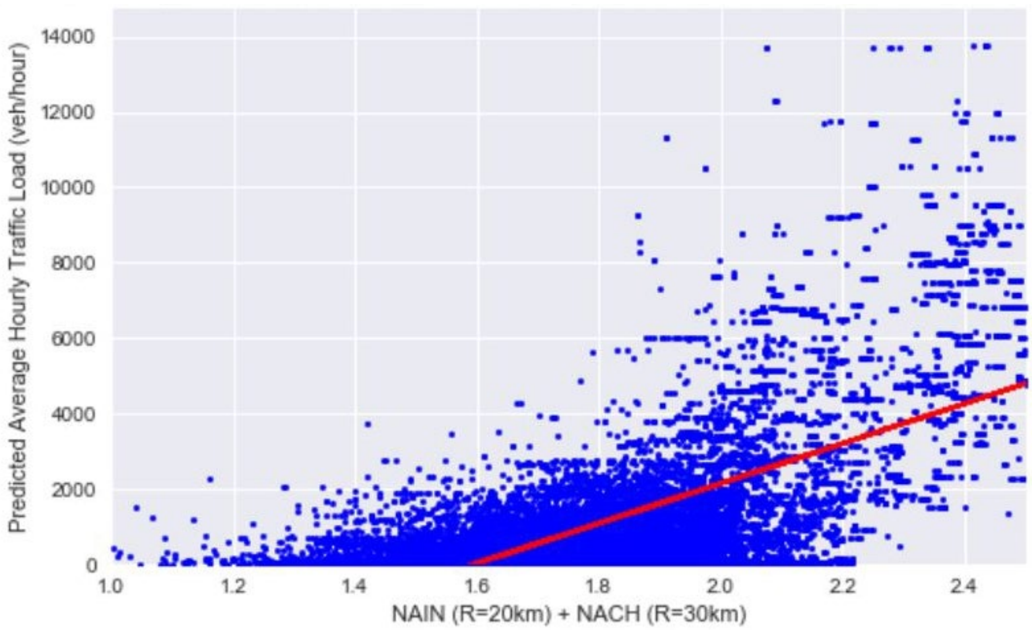


Figure 39, scatterplot with the sum of unweighted NAIN (radius = 20 km) and NACH (radius = 20 km)

The combined network centrality map and the predicted traffic loads map are shown in figures 40 and 41 on the next two pages. The centrality map (figure 40) shows the streets that are potentially more travelled by the collective to-movement and through-movement based on spatial configuration of the urban grid. See the spatial analysis chapter and appendix A6 for the individual network centrality maps.

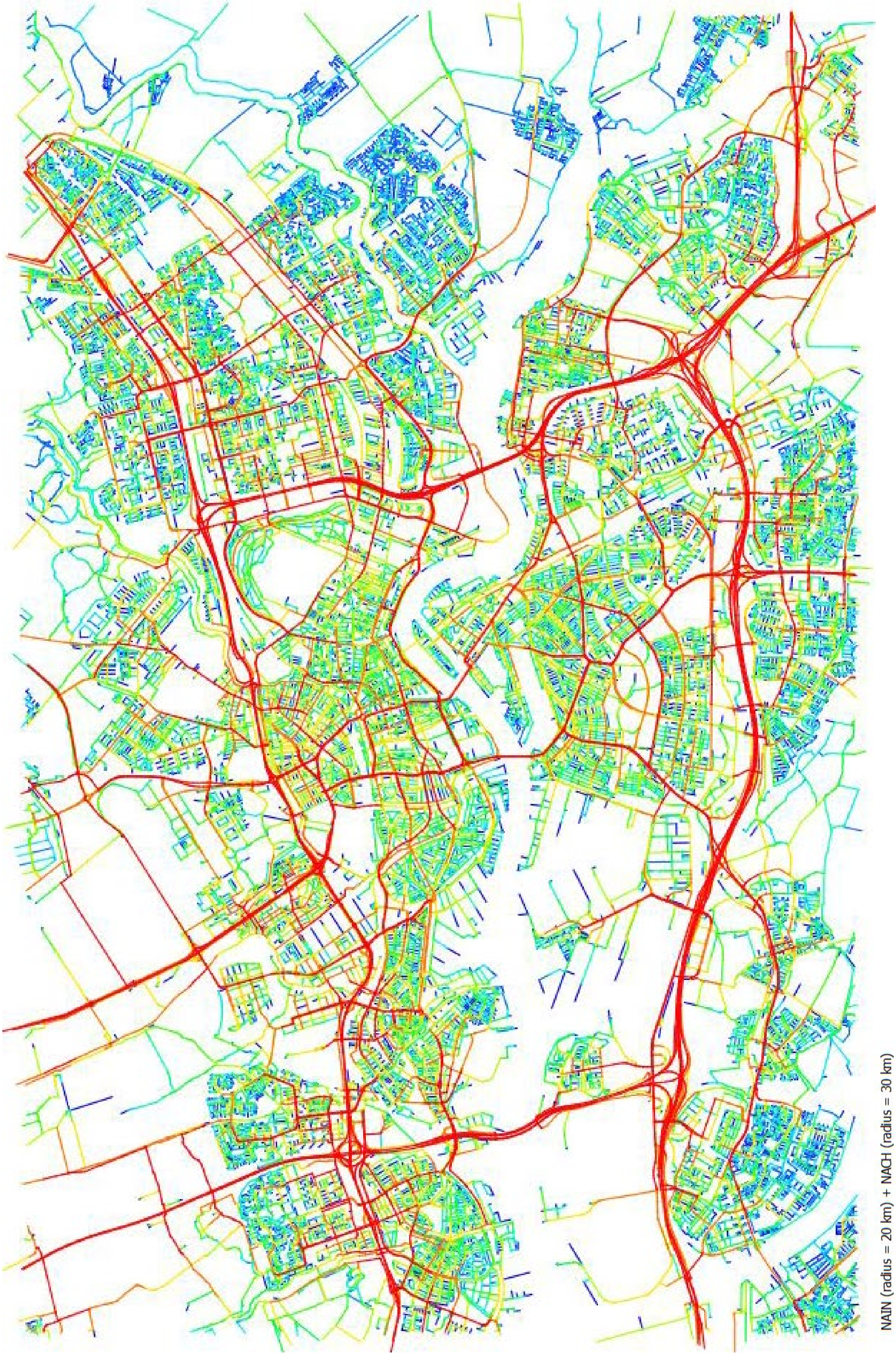


Figure 40, Combined NAIN (radius = 20 km) and NACH (radius = 30 km) map

Predicted Average Hourly Traffic Load (veh/hour)

- 0 - 19
- 19 - 84
- 84 - 189
- 189 - 426
- 426- 1140
- 1140 - 13787

Figure 41, Predicted average hourly traffic load map of Rotterdam

4.1 Weighted Simple Linear Regression Analysis

In the weighted simple linear regression analysis the network centrality measures of each street segment are multiplied by its road characteristics; segment length, speed limit and road capacity. The r and R^2 of each road characteristic with the predicted traffic loads are also calculated separately to see their contribution when applied as an independent weighting function (see table 5). The simple linear regression analysis is again conducted for a various range of spatial scales (see tables 6, 7 and 8).

Road Characteristics Weighting	r	R^2
Segment Length	0.20	0.04
Speed Limit	0.72	0.52
Road Capacity	0.84	0.70

Table 5, r and R^2 values with individual road characteristics and predicted traffic loads

Spatial Scale	Angular Betweenness (AC) x Segment Length		Angular Betweenness (AC) x Speed Limit		Angular Betweenness (AC) x Road Capacity	
Radius (m)	r	R^2	r	R^2	r	R^2
1000	-0.13	0.02	0.01	0.00	-0.04	0.00
2500	-0.02	0.00	0.14	0.02	0.14	0.02
5000	0.20	0.04	0.37	0.14	0.40	0.16
7500	0.30	0.09	0.48	0.23	0.51	0.26
10000	0.37	0.13	0.57	0.33	0.59	0.35
15000	0.43	0.19	0.65	0.42	0.67	0.45
20000	0.43	0.19	0.64	0.41	0.67	0.45
30000	0.43	0.18	0.62	0.38	0.64	0.41

Table 6, r and R^2 values with weighted Angular Betweenness Centrality measures

Spatial Scale	Normalized Angular Betweenness (NACH) x Segment Length		Normalized Angular Betweenness (NACH) x Speed Limit		Normalized Angular Betweenness (NACH) x Road Capacity	
Radius (m)	r	R^2	r	R^2	r	R^2
1000	0.17	0.03	0.68	0.46	0.78	0.61
2500	0.20	0.04	0.71	0.51	0.81	0.65
5000	0.23	0.05	0.74	0.54	0.82	0.68
7500	0.25	0.06	0.75	0.57	0.84	0.70
10000	0.26	0.07	0.76	0.58	0.85	0.72
15000	0.27	0.08	0.78	0.60	0.86	0.73
20000	0.28	0.08	0.78	0.61	0.86	0.74
30000	0.29	0.08	0.79	0.62	0.86	0.74

Table 7, r and R^2 values with weighted Normalized Angular Betweenness Centrality measures

Spatial Scale	Angular Closeness (NAIN) x Segment Length		Angular Closeness (NAIN) x Speed Limit		Angular Closeness (NAIN) x Road Capacity	
Radius (m)	**r**	**R^2**	**r**	**R^2**	**r**	**R^2**
1000	0.28	0.08	0.68	0.46	0.75	0.56
2500	0.28	0.08	0.76	0.58	0.84	0.70
5000	0.30	0.09	0.78	0.61	0.86	0.73
7500	0.32	0.10	0.78	0.61	0.87	0.75
10000	0.32	0.10	0.78	0.60	0.87	0.76
15000	0.31	0.10	0.77	0.60	0.88	0.77
20000	0.31	0.10	0.78	0.61	0.88	0.78
30000	0.30	0.09	0.77	0.60	0.88	0.78

Table 8, r and R^2 values with weighted Angular Closeness Centrality measures

[Normalized Angular Betweenness (NACH) + Angular Closeness Centrality (NAIN)] x Road Characteristics	r	R^2
NACH (radius = 30km) + NAIN (radius = 20km)	0.67	0.44
[NACH (radius = 30km) + NAIN (radius = 20km)] **x** Segment Length	0.30	0.09
[NACH (radius = 30km) + NAIN (radius = 20km)] **x** Speed	0.79	0.62
[NACH (radius = 30km) + NAIN (radius = 20km)] **x** Road Capacity	0.88	0.77

Table 9, r and R^2 values with weighted NAIN (radius = 20 km) + NACH (radius = 30 km)

The application of road capacity as a weighting function leads to the largest increase of the r and R^2 compared to the unweighted simple lineair regression analysis. The segment length is an unsuitable weighting function due to its adverse effect on the correlation with predicted traffic load. The combined angular closeness and normalized angular betweenness centrality measures do not significant change the results (see table 9). The scatterplot of the weighted NAIN (radius = 20 km) + NACH (radius = 30 km) is shown in the figure 42 below.

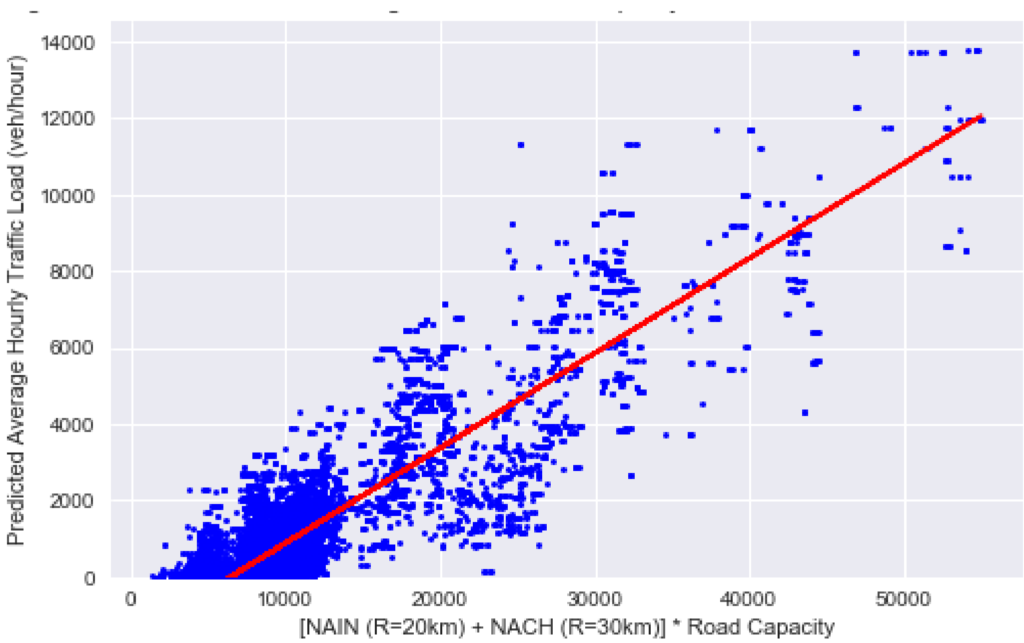


Figure 42, scatterplot with the sum of weighted NAIN (radius = 20 km) and NACH (radius = 20 km) by road capacity

5. Conclusion

The research has proven that the spatial configuration of the street network has a considerable effect on the movement patterns of motorized vehicles. All individual angular network centrality measures have a moderate positive correlation with the predicted traffic loads at spatial scales with radii greater than 15 km. These spatial scales relate the average daily travelling distance of 29.1 km by cars in The Netherlands. (CBS Stateline, 2017) The sum of the angular betweenness centrality and angular closeness centrality increases both the Pearson correlation coefficient, r and coefficient of determination, R^2. This confirms the hypothesis that the total movement can be regarded is a summation or at least a function of the to-movement and through-movement. The combined angular betweenness centrality (NACH) and normalized angular closeness centrality (NAIN) with radii 30 km and 20 km respectively give the highest unweighted r of 0.67 and R^2 of 0.44. A Pearson correlation coefficient, r above 0.70 can be considered as strong positive. This indicates that the traffic loads, the dependent variable can be explained for 44 % by the spatial configuration of the street network of Rotterdam. This also means that the street network of Rotterdam is still predominately driven by traffic needs. The R^2 value is below 0.70 meaning that the linear relationship is not statistically significant for accurately predicting the traffic loads. Besides that the spatial analysis is done on a static network there are multiple other independent variables that may contribute to the degree of traffic flow through individual street segments. A multiple linear regression analysis in combination with a principal component analysis (PCA) is required to understand the percentage contribution to explanation of the traffic load (dependent variable, Y) by multiple underlying components (independent variables, X). A set of independent variables can also be inter-dependent to each other. Although the correlation analysis is not able directly capture the non-directive characteristics of the street network of Rotterdam; the policy makers, traffic planners and engineers, and spatial planners that are responsible for the infrastructural changes.

Weighting functions need to be incorporated in the network centrality measures in order to potentially use space syntax as a valid traffic assessment tool. The application of road characteristics; segment length, speed limit and road capacity as weighting functions have a vast effect on the simple linear regression analysis. The network centrality measures weighted by the road capacity result in the largest increase of the coefficients of determination, R^2 with much smaller variances with the predicted traffic loads. The weighted NAIN with radii 20km and 30 km give the most promising r of 0.88 and a R^2 of 0.78. The weighted combination of NAIN (radius = 20 km) and NACH (radius = 30 km) produces identical results with an r of 0.88 and a R^2 of 0.77. Ideally the R^2 should be as close to 1 as possible although the predicted traffic load measures from the four step macroscopic traffic model may also not be fully corresponding with real life traffic count observations. As mentioned before, traffic loads and movement patterns can only be captured to a certain degree and will remain very dynamic just as the relations shown in the adapted circle of Wegener (see Appendix A2).

6. Recommendations and Future Research

Multiple Regression Analysis and Principal Component Analysis

As mentioned in the conclusion, there must be done more research to discover how the spatial configuration of the street network but also the spatial morphology of buildings and public space affect movement patterns in the city of Rotterdam. A multiple regression analysis in combination with principle component analysis (PCA) can be used to measure the linear inter-dependence between different variables and how much they individually contribute to predicting the level of movement by different modes of transport using the street network (e.g. pedestrians, cyclist and motorized vehicles). The PCA shows how many of the independent variables are needed to explain the predicted traffic loads. This method allows a dimension reduction. The independent variables that contribute the most (high correlation coefficient and low variances) besides the betweenness and closeness centrality measures can be used a weighting functions to validate space syntax as a traffic assessment tool. The suggested independent variables are attraction variables based on (GIS) location-based density and differentiation (L. Marcus et. al, 2017); the intensity of different land-uses, population density and spatial density of buildings. Kernel density estimation (KDE) can be used for comparing the data of land-use intensity and population density with the network centrality measures from space syntax and the predicted traffic loads. KDE is a non-parametric way to estimate the probability density function of a random variable. (S. Porta et. al, 2009) In QGIS you can create KDE heat maps (see appendix A8) within a given (metric) radius to aggregate the density so that both datasets can be matched and statistically compared. Furthermore, the spatial density is quantified by the measures of floor space index (FSI = Gross floor Area/ Aggregated Plot Area) and Ground Space Index (GSI = Building Footprint Area/Aggregated Plot Area) using Spacematrix analysis. It measures the spatial capacity of buildings to differentiate functions and host mixed-uses (residential, amenities and working). (Van Nes et. al, 2012)

Data Preparation for Spatial Analysis

In order to improve the unweighted spatial analysis, the road centre line map should be filtered by different road categories. Street segments that are inaccessible for motorized vehicles should be removed from the dataset. Vice versa for the spatial analysis of urban pedestrian and/or cyclist movement patterns. It may occur that the road centre line dataset contains mistakes. The techniques of automatic snapping and breaking of lines at the exact geographic location of junctions, tunnels and bridges should be further developed to guarantee that the shortest paths are realistic route choices.

Observed Traffic Counts

Moreover the links in the macroscopic traffic model are sometimes aggregated in zones and not available for all streets in the network, especially for the lower categorized streets in urban neighbourhoods. There are also many links in the macroscopic traffic model that do not geographically match with the road centre lines as shown in figure 32. Therefore it also suggested to compare the network centrality measures with a large number of observed traffic count. As additional research the Spearman’s rank correlation and scatterplot for the network centrality measures and the daily observed traffic count at 34 locations in Rotterdam North can be found in appendix A9. However, the number of observation are insufficient to state valid conclusions.

References

Andersen, H. S. (2002). Excluded Places: The Interaction Between Segregation, Urban Decay and Deprived Neighbourhoods. *Housing, Theory and Society*, *19*(3-4), 153–169. https://doi.org/10.1080/140360902321122860

Bertolini, L., Le Clercq, F., & Kapoen, L. (2005). Sustainable accessibility: a conceptual framework to integrate transport and land use plan-making. Two test-applications in the Netherlands and a reflection on the way forward. *Transport Policy*, *12*(3), 207–220. https://doi.org/10.1016/j.tranpol.2005.01.006

Bertolini, L. (2012). Integrating Mobility and Urban Development Agendas: a Manifesto, disP – The Planning Review, 48:1, 16-26

CBS StatLine. (n.d.). Personenmobiliteit in Nederland; vervoerwijzen en reismotieven, regio's [Dataset]. Retrieved June 12, 2019, from https://statline.cbs.nl/StatWeb/publication/?DM=SLNL&PA=83500ned

CBS. (n.d.). Bevolking; ontwikkeling in gemeenten met 100 000 of meer inwoners, 2018 [Dataset]. Retrieved June 16, 2019, from https://statline.cbs.nl/StatWeb/publication/?VW=T&DM=SLNL&PA=70748NED&D1=0,2,4,16,18,20,22,24&D2=a&D3=0&D4=a&D5=l&HD=090707-1905&HDR=T&STB=G4,G2,G1,G3

Dalton, N. (2001). *Fractional Configurational Analysis and a solution to the Manhattan problem.* Retrieved from https://www.researchgate.net/publication/238787585_Fractional_Configurational_Analysis_and_a_solution_to_the_Manhattan_problem

Gibson, J. J. (1979). *The Ecological Approach to Visual Perception*. Retrieved from https://books.google.nl/books/about/The_Ecological_Approach_to_Visual_Percep.html?id=DrhCCWmJpWUC&redir_esc=y

Hillier, B. (2002). A theory of the city as object: or, how spatial laws mediate the social construction of urban space. *URBAN DESIGN International*, *7*(3-4), 153–179. https://doi.org/10.1057/palgrave.udi.9000082

Hillier, B. (2007). *Space is the machine*. Retrieved from http://discovery.ucl.ac.uk/3881/1/SITM.pdf

Hillier, B., & Hanson, J. (1984). *The Social Logic of Space.*. https://doi.org/10.1017/CBO9780511597237

Hillier, B., & Iida, S. (2005). Network and Psychological Effects in Urban Movement. *Spatial Information Theory*, , 475–490. https://doi.org/10.1007/11556114_30

Hillier, B., Penn, A., Hanson, J., Grajewski, T., & Xu, J. (1993). Natural movement: or, configuration and attraction in urban pedestrian movement. *Environment and Planning B: Planning and Design*, *20*(1), 29–66. https://doi.org/10.1068/b200029

Hillier, B., & Serra, M. (2017). *Spatial Configuration and Vehicular Movement: a nationwide correlational study*. Retrieved from http://www.11ssslisbon.pt/docs/proceedings/papers/122-2.pdf

Hillier, B., Yang, T., & Turner, A. (2012). *Normalising least angle choice in Depthmap and how it opens new perspectives on the global and local analysis of city space*. Retrieved from https://www.researchgate.net/publication/312488636_Normalising_least_angle_choice_in_Depthmap_and_how_it_opens_new_perspectives_on_the_global_and_local_analysis_of_city_space

Koch, D., Marcus, L., & Steen, J. (2009). *7th International Space Syntax Symposium: Proceedings*. Retrieved from http://sss7.org/Proceedings/07%20Urban%20Structures%20and%20Spatial%20Distribution/120_vanNes.pdf

Kruger, M. (1989). *On node and axial grid maps: distance measures and related topics* (Presented at European Conference on the Representation and Management of Urban Change). Retrieved from http://discovery.ucl.ac.uk/1011/1/Kruger_1989_OnNodeAndAxialGrid.pdf

Marcus, L., Berghauser Pont, M., Stavroulaki, G., & Bobkova, J. (2017a). Location-based density and diversity – adding attraction variables to space syntax. *Proceedings 24th ISUF 2017 - City and Territory in the Globalization Age*, . https://doi.org/10.4995/isuf2017.2017.5706

Marcus, L., Berghauser Pont, M., Stavroulaki, G., & Bobkova, J. (2017b). Location-based density and diversity – adding attraction variables to space syntax. *Proceedings 24th ISUF 2017 - City and Territory in the Globalization Age*, . https://doi.org/10.4995/isuf2017.2017.5706

MRDH. (n.d.). Verkeersmodel (Traffic Model) Metropoolregio Rotterdam Den Haag [Dataset]. Retrieved April 20, 2019, from https://mrdh.nl/project/verkeersmodel

Municipality of Rotterdam. (n.d.). Tellingen (Traffic Counts) GDW [Dataset]. Retrieved May 10, 2019, from http://rotterdamopendata.nl/dataset

Patterson, J. L. (2016). Traffic modelling in cities – Validation of space syntax at an urban scale. *Indoor and Built Environment*, *25*(7), 1163–1178. https://doi.org/10.1177/1420326x16657675

Penn, A., Hillier, B., Banister, D., & Xu, J. (1998). Configurational modelling of urban movement networks. *Environment and Planning B: Planning and Design*, *25*(1), 59–84. https://doi.org/10.1068/b250059

Peponis, J. (2001). Interacting questions and descriptions. How do they look from here? *Proceedings of the Third Space Syntax Symposium, Atlanta*, . Retrieved from https://www.ucl.ac.uk/bartlett/3sss/papers_pdf/00_peponis.pdf

Porta, S., Strano, E., Iacoviello, V., Messora, R., Latora, V., Cardillo, A., Scellato, S. (2009). Street Centrality and Densities of Retail and Services in Bologna, Italy. *Environment and Planning B: Planning and Design*, *36*(3), 450–465. https://doi.org/10.1068/b34098

Rijkswaterstaat. (n.d.). Nationaal Wegen Bestand (NWB) 2018 [Dataset]. Retrieved April 18, 2019, from https://www.rijkswaterstaat.nl/apps/geoservices/geodata/dmc/nwb-wegen/geogegevens/shapefile/Nederland_totaal/01-12-2018/Wegvakken/

Space Syntax. (n.d.). Software | Space Syntax Network [Dataset]. Retrieved April 18, 2019, from http://www.spacesyntax.net/software/

Spatial Morphology Group. (n.d.). *Spatial Morphology Group Lectures* [Video file]. Retrieved April 20, 2019, from https://www.youtube.com/channel/UCkPuGfW-nxdF7P9nWrjNSow

Sthåle, A. (2012). Place Syntax Tool (PST), in Angela Hull, Cecília Silva and Luca Bertolini (Eds.) Accessibility Instruments for Planning Practice. COST office, pp. 173-178

Stavroulaki, G., Marcus, L., Berghauser Pont, M., & Nilsson, L. (2017). *REPRESENTATIONS OF STREET NETWORKS IN SPACE SYNTAX: Towards flexible maps and multiple graphs*. Retrieved from https://pdfs.semanticscholar.org/7339/d9bcd51dd8bdb945a74037be72059f3739dc.pdf

Systematica, & Transform Transport. (2018). *Correlation between space syntax and vehicle traffic volumes*. Retrieved from https://issuu.com/systematica/docs/190115_correlation_ssy_and_traffic_

Turner, A. (2005). *Being in space and space in being*. Retrieved from http://spacesyntax.tudelft.nl/media/Long%20papers%20I/alasdair%20turner.pdf

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*, *34*(3), 539–555. https://doi.org/10.1068/b32067

UCL Space Syntax. (n.d.). Space Syntax Online Training Platform. Retrieved June 10, 2019, from http://otp.spacesyntax.net/

Van de Werken, A. (2018). *Verkeersmodel MRDH 2.0 Technische Rapportage* (Figure 2.2: Werking van het verkeersmodel (page 6)). Retrieved from https://mrdh.nl/system/files/projectbestanden/rapport%20Verkeersmodel%20MRDH%202.0%20-%20001594.20181026.R1.02.pdf

Van Nes, A. (2014). Space Syntax in Theory and Practice. *Geodesign by Integrating Design and Geospatial Sciences*, , 237–257. https://doi.org/10.1007/978-3-319-08299-8_15

Van Nes, A., Berghauser Pont, M., & Mashhoodi, B. (2012). Combination of Space syntax with spacematrix and the mixed use index: The Rotterdam South test case. *Eighth International Space Syntax Symposium Santiago, PUC , 2012*, . Retrieved from https://www.researchgate.net/publication/239844249_Combination_of_Space_syntax_with_spacematrix_and_the_mixed_use_index_The_Rotterdam_South_test_case

Wegener, M., & Fürst, F. (1999). Land-Use Transport Interaction: State of the Art. Deliverable D2a of the project TRANSLAND (Integration of Transport and Land use Planning). Dortmund: Universität Dortmund.

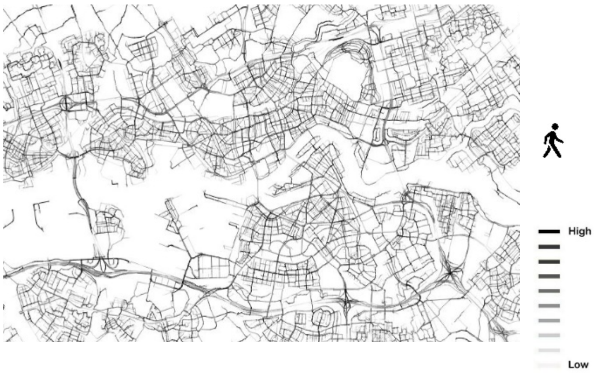
Appendix

A1: Spatial Scale and Mode Choices

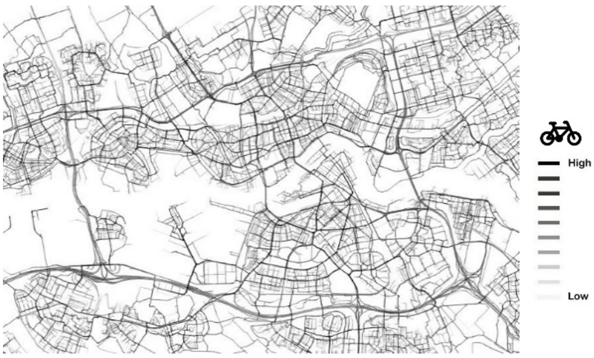
The average travelling distance per mode choice for the Netherlands can be found in the CBS StatLine Database (2017): Personenmobiliteit in Nederland; vervoerwijzen en reismotieven, regio's

R = 500m: 'very small scale, highlight streets and particular junctions that are ideal for community services, small local businesses that require high pedestrian footfall' (Systematica, 2018)

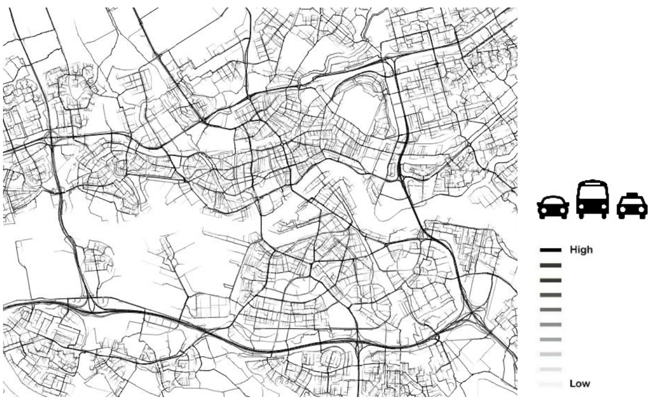
R = 1000m: 'Ideal distance everyone is willing to walk on foot. The distance that walking is more convenient than all other modes. The spatial analysis shows potential area for being the centre of neighbourhood activities' (Systematica, 2018)



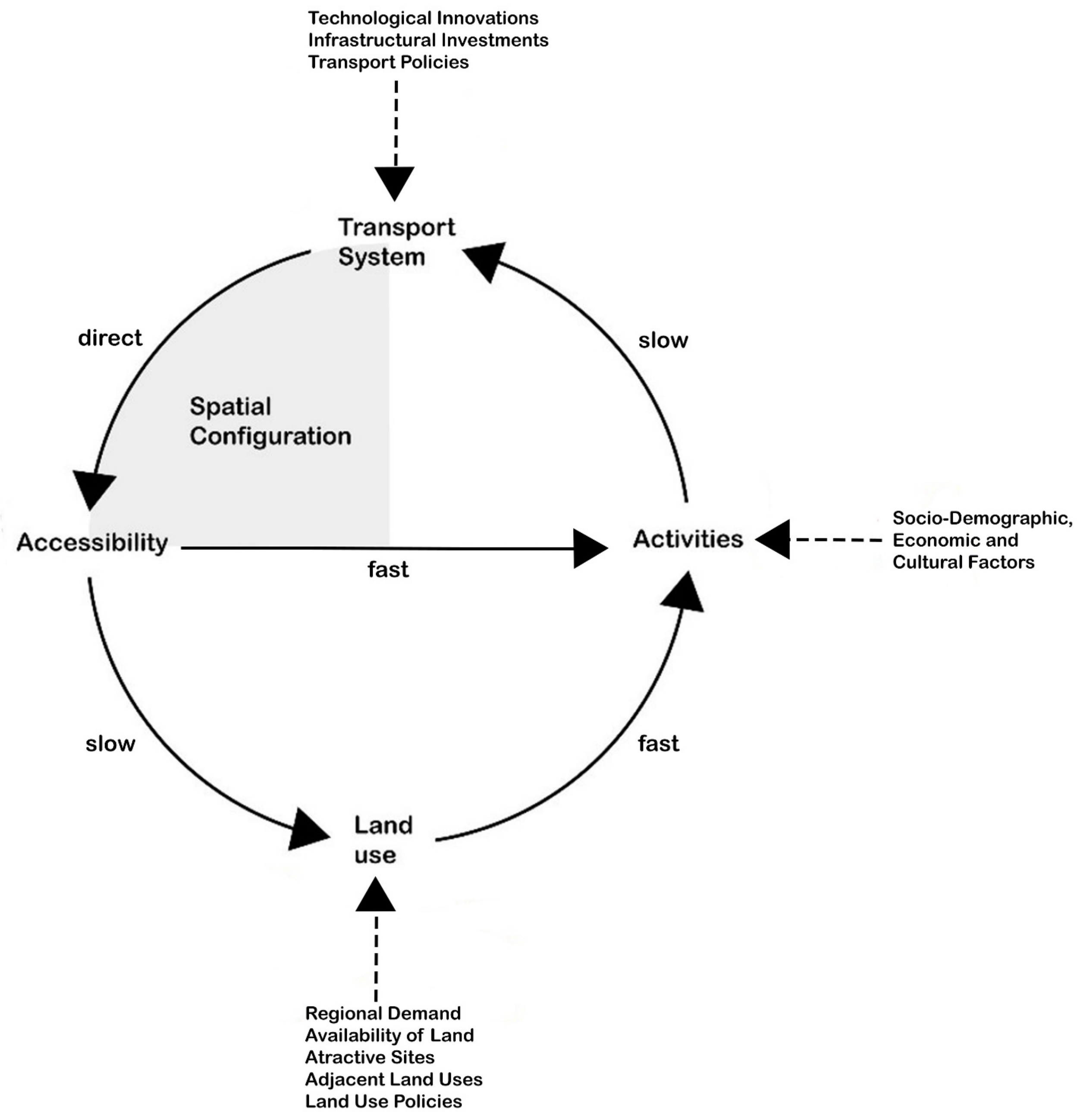
R = 2500m: 'The most convenient routes for bicycles and other small electric vehicles' (Systematica, 2018)



R > 2500: Routes used to 'preliminary identify convenient routes for long distance movements, most likely by car or bus at urban scale' (Systematica, 2018)



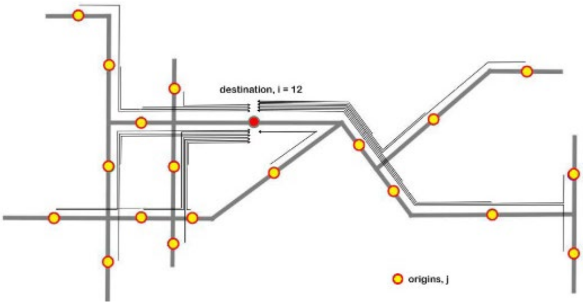
A2: Adapted circle of Wegener with external factors



(M. Wegener & F. Fürst, 1999; adapted by L. Bertolini, 2012)

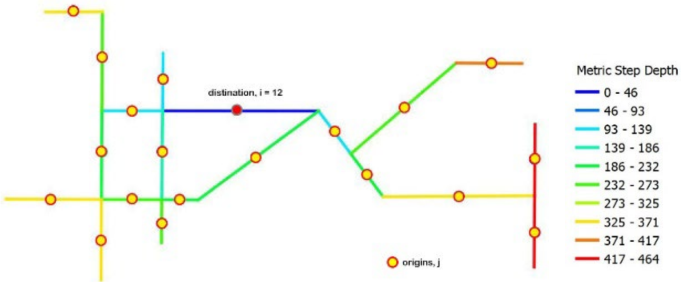
A3: Metric and Topological Network Centrality Measures of Toy Street Network

Least Length Path (Metric)



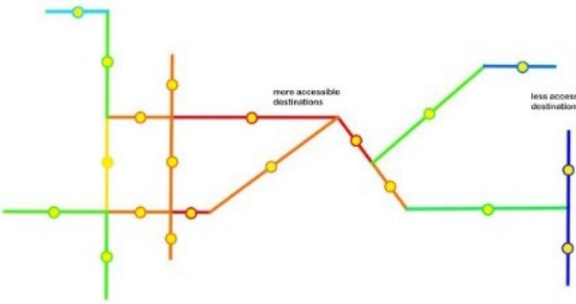
Least Length Paths from all origins (j) to destination node (i = 12)

→ Metric Step Depth

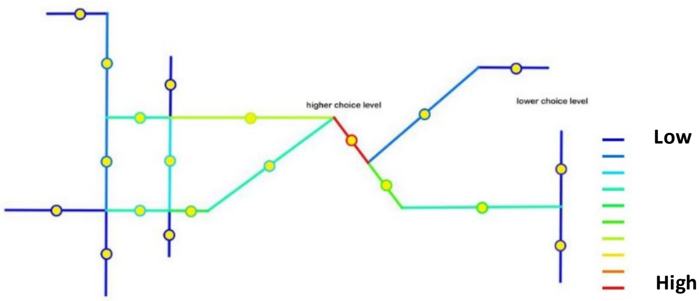


Metric Step Depth from all origins (j) to destination node (i = 12)

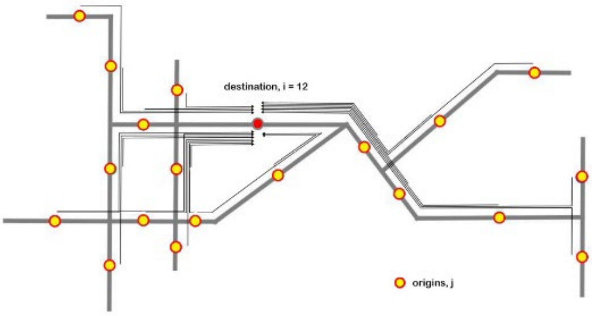
Metric Closeness Centrality (or Network Integration as known in space syntax community)



Metric Betweenness Centrality (or Network Betweenness as known in space syntax community)

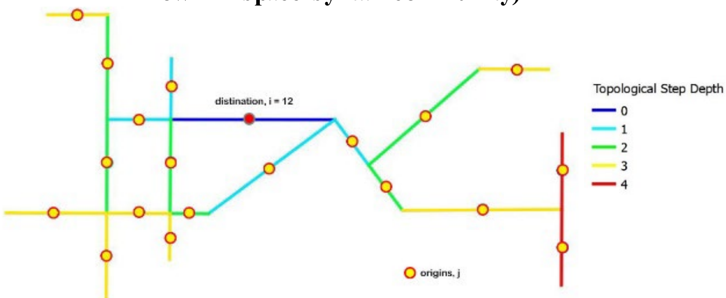


Fewest Turns Path (Topological)



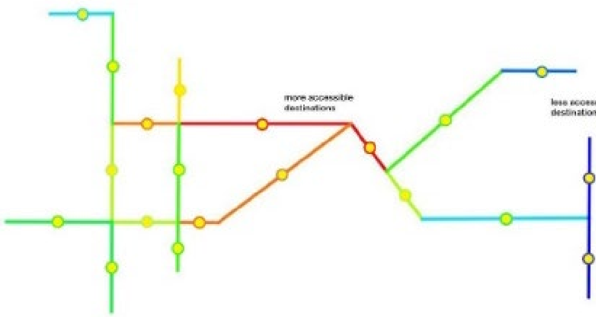
Fewest Turns Paths from all origins (j) to destination node (i = 12)

→ Topological Step Depth (or axial step depth as known in space syntax community)

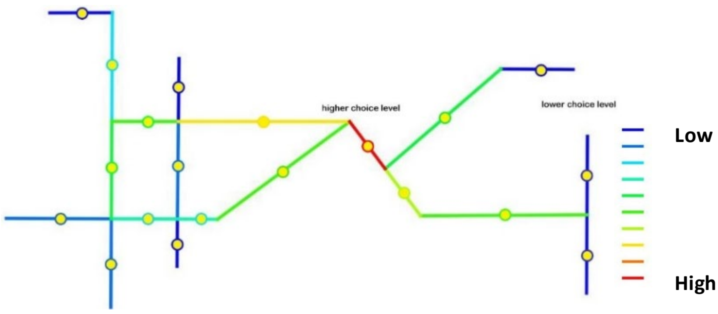


Topological (Axial) Step Depth from all origins (j) to destination (i = node 12)

Topological Closeness Centrality (or Axial Integration as known in space syntax community)



Topological Betweenness Centrality (or Axial Betweenness as known in space syntax community)



A4: Previous Case Studies

Previous case studies on using the space syntax approach for correlation analysis with vehicular movement are very valuable sources. The case studies should reach a level of consistency so that the research is reproducible for new test cases. The new findings and recommendations of the following two case studies have been used to improve and adjust the methodology of this research.

1. City of Milan Case Study (Systematica, 2018)

The city of Milan case study by Systematica focused on using angular betweenness (or angular choice as known in the space syntax community) and normalized angular betweenness (NACH) to compare it with forecasted traffic loads from the CUBE four step macroscopic traffic model. High correlation levels were recorded between traffic loads and angular choice values if 'normalization' was applied (NACH). Even higher correlation values are recorded when NACH values are multiplied by road capacities with a coefficient of determination, R^2 of 0.7129. Other weighting variables such as segment length and speed also improved the results. The spatial scale with a radius of 20 km proved to be the best predictor for the macroscopic traffic volumes. Systemtica recommended to test their methodology with a different test case and compare the results. The results from the Rotterdam test case produces higher R^2 values than the Milan case study when road characteristics are used as the weighting function which could indicate that the traffic planning may be better organised to meet the city's traffic needs. Furthermore the recommend to carry out additional for different road categories besides urban roads and weigh betweenness centrality (choice) values with different parameters such as land use and population.

2. City of Cardiff Case Study (J. Patterson, 2016)

The city of Cardiff case study by J. Patterson indicate when using road weightings based on national road classification, the correlation between the different closeness centrality measures (or integration) and the average hourly traffic flow are significantly improved. This case study used traffic counts instead of data from a macroscopic traffic model. J. Patterson recommends weighting based on road classification to global closeness centrality values as the correlation values are the most consistent.

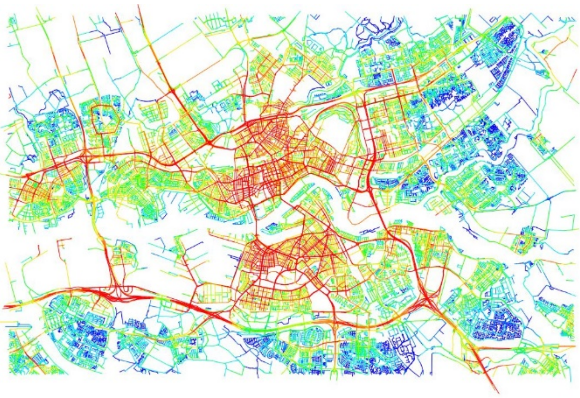
A5: Road centre lines extraction and modification steps

The road centre line dataset can be extracted from different GIS databases, or axial lines can be manually drawn for a small study areas (e.g. local neighbourhood) with autoCAD although it can very time-consuming. After the road centre line data (e.g. of the entire national road network) has been extracted and imported in QGIS (Geographic Information System Software), the lines within the study area have to be selected plus an additional buffer zone depending on the spatial scales for the spatial analysis. There are likely to be disconnected lines at the edges of the buffer zone when the map is extracted. These isolated lines have to be removed and can be identified by running a node count through an axial analysis for infinite spatial scale (radius = n) on the DepthMapX software. Before doing so, the road centre line map needs to be converted to an axial map. The axial analysis will provide a node count for each line; the number of lines that are connected within a system.

The isolated axial lines will have a much lower. Once the isolated lines are removed you can also unlink lines that are not supposed to intersect as a junction or interchange. For this research it is assumed that all lines are correctly broken at the junctions and that there are no major mistakes due to the project's limited time span. Snapping and unlinking of lines can be time-consuming at urban/regional scale unless you have the exact location of the intersection nodes available on GIS. In order to do an angular segment analysis for the angular network centrality measures, the axial map has to be converted to a segment map. The segment map should be saved as a TAB file so that Place Syntax Tool Plug-In (PST) in QGIS can run the different spatial analysis. With the PST is much quicker than the DepthMapX software in producing spatial analysis with manually selected the definition of distance and spatial scale radius. Unlike the DepthmapX, the PST does not allow an infinite spatial scale (radius = n).

A6: Network Centrality Maps of Intermediate Spatial Scales

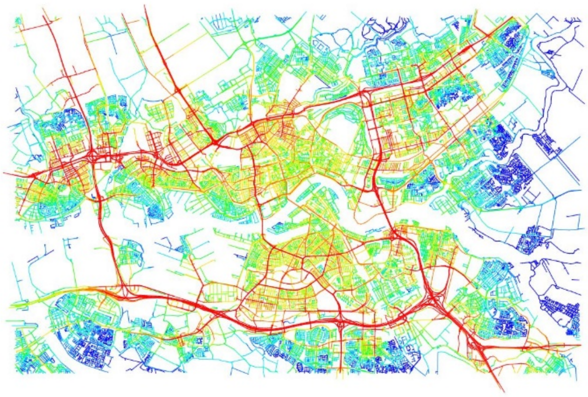
Angular Closeness Centrality Maps



Radius = 2500 m

Radius = 5 km

Radius = 7500 m



Radius = 10 km

Radius = 15 km

Radius = 20 km

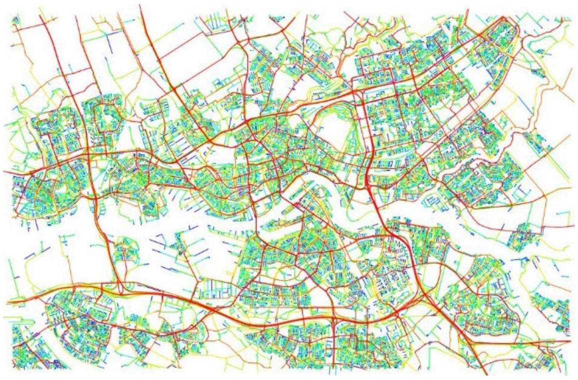
Angular Betweenness Centrality Maps

Radius = 2500 m

Radius = 5 km

Radius = 7500 m

Radius = 10 km



Radius = 15 km

Radius = 20 km

Normalized Angular Betweenness Centrality Maps

Radius = 2500 m

Radius = 5 km

Radius = 7500 m

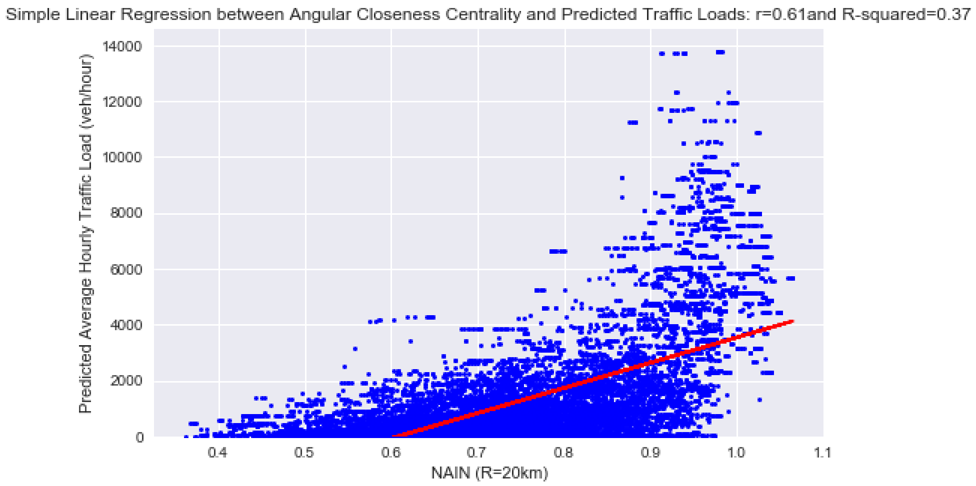
Radius = 10 km

Radius = 15 km

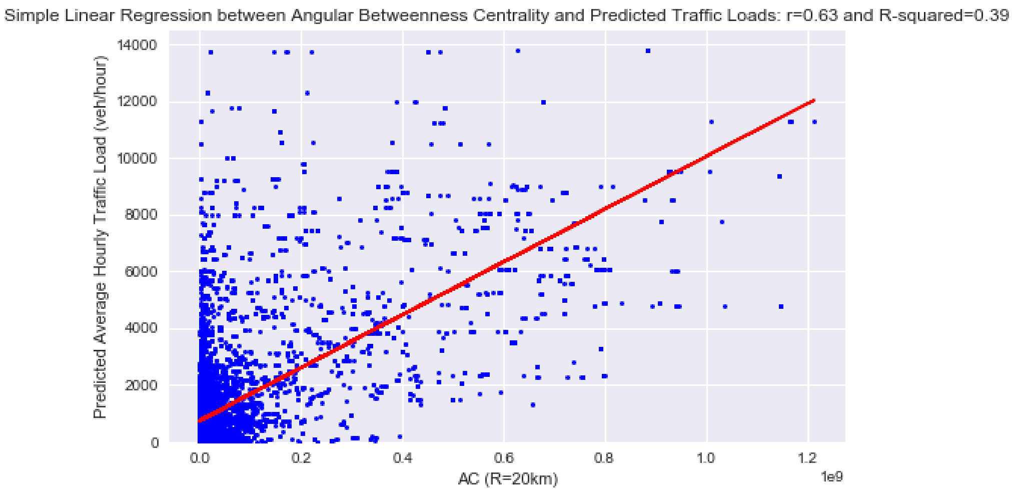
Radius = 20 km

A7: Scatterplots of highest correlation individual network centrality measures and predicted traffic loads

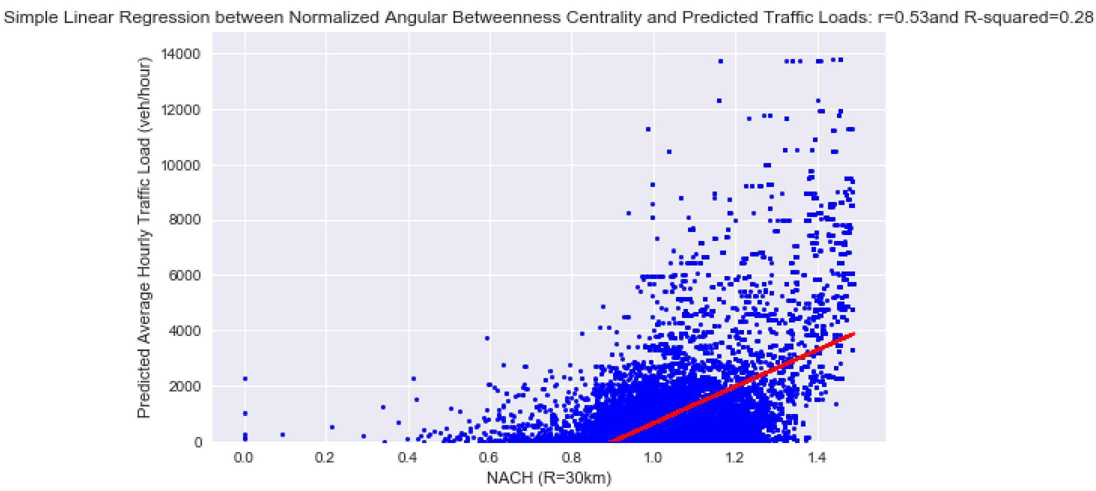
Angular Closeness Centrality (radius = 20 km)



Angular Betweenness Centrality (radius = 20 km)

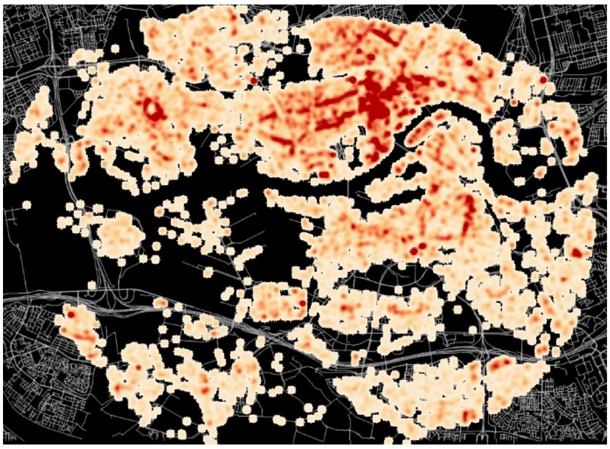


Normalized Angular Betweenness Centrality (radius = 30 km)



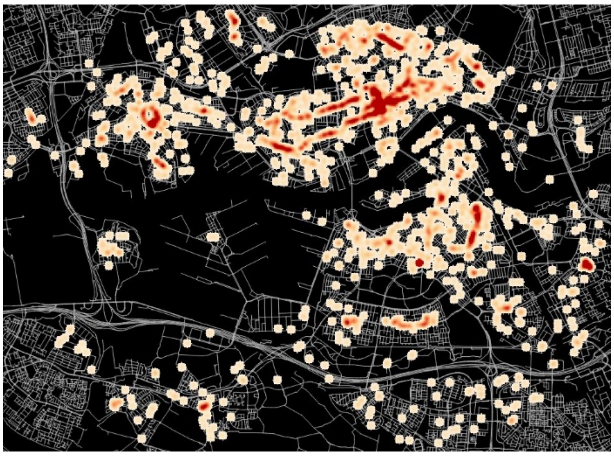
A8: Kernel Density Estimation Heat Maps (radius = 100 m)

KDE Heat Map of businesses (Municipality of Rotterdam, 2014)

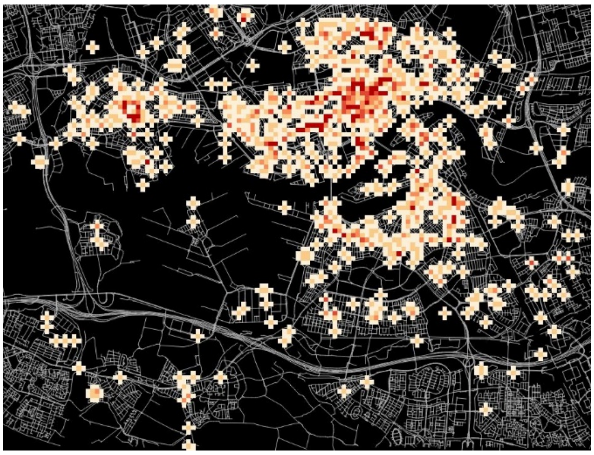


KDE Heat Map of office buildings (Municipality of Rotterdam, 2014)

KDE Heat Map of retail services (Municipality of Rotterdam, 2014)



KDE Heat Map of food and drinks locations (Municipality of Rotterdam, 2014)



KDE Heat Map of population (CBS, 2017)

KDE businesses (radius = 100 m)
- 0
- 4.66
- 9.33
- 14
- 18.7

KDE offices (radius = 100 m)
- 0
- 18.2
- 36.4
- 54.6
- 72.9

KDE retail (radius = 100 m)
- 0
- 2.31
- 4.61
- 6.92
- 9.23

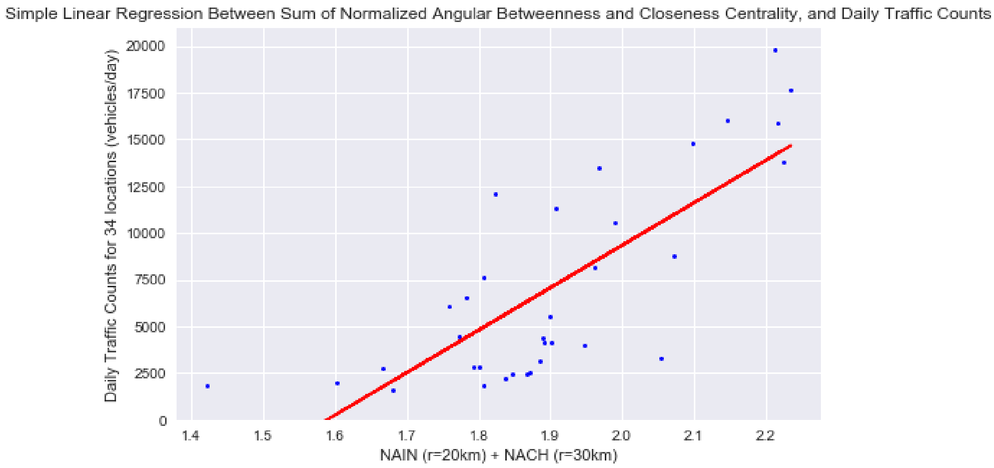
KDE Eating and Drinking (radius = 100 m)
- 0
- 0.999
- 2
- 3
- 4

KDE population (radius = 100 m)
- 0
- 293.6
- 587.1
- 880.7
- 1174

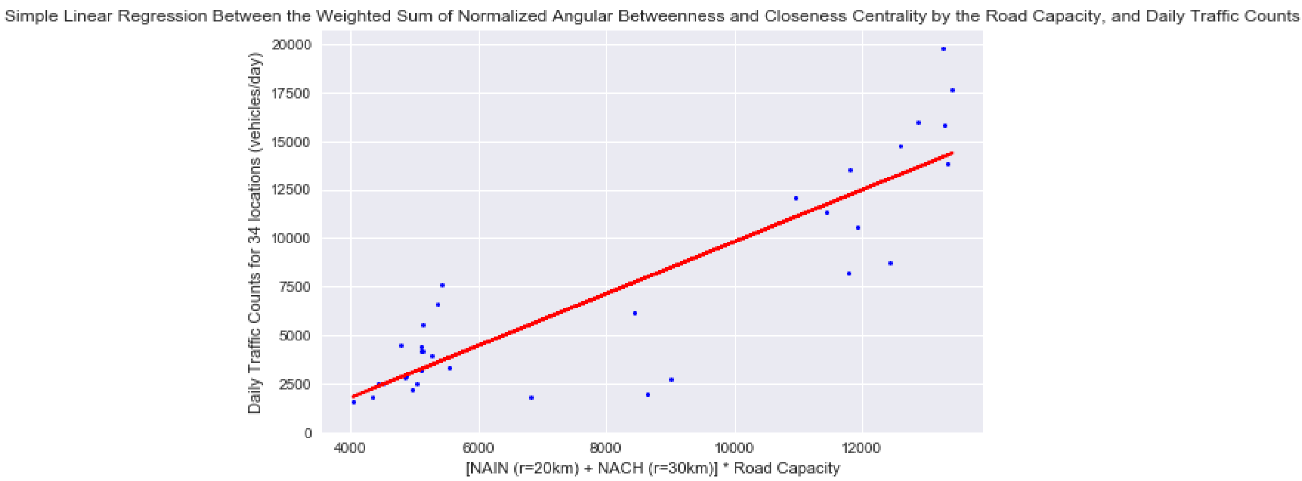
A9: Spearman’s Rank Coefficient Network Centrality Measures and Observed Traffic Counts

Map with 34 traffic count observation locations (red marks) in Rotterdam-North. The data contains the average total day traffic count (vehicles/day) with daily measures between Mon 1 June and Sunday 7 June 2015. (Rotterdam Open Data Store, 2015)

Spearman’s rank correlation coefficient, r = 0.74



Spearman’s rank correlation coefficient, r = 0.82



A10: Methodology Manual Steps

Steps	Data Source	Description	Tools/Software
1. Data Preparation	NWB Road Centre Lines & CBS 2018 study area boundaries	• Selection of Study Area: Rotterdam urban area + 30 km buffer • Convert Road centre line map to axial map • Removal of disconnected/isolated lines • Convert to segment map	QGIS 2.18.16, DepthMapX 0.35
	Location-based density and differentiation data: CBS 2018 & Rotterdam Municipality GIS Plot and Building Info*	• Import shapefile data into QGIS and create Kernel Density Estimation (KDE) Heat Maps* (See appendix A9) • Match KDE values to road centre line segments*	
	V-MRDH 2.0 OmniTRANS Project	• Export macroscopic model links as shapefile data with traffic load, speed limit and road capacity attribute data and import in QGIS • Match with road centre line segments with the same CRS projection and within a 5 m buffer	omniTRANS 8.0 and QGIS 2.18.16
2. Spatial Analysis		• Run Unweighted Angular Segment Analysis (Angular Closeness Centrality, Angular Betweenness Centrality and Normalized Angular Betweenness Centrality) • Apply different spatial scales (radius = 1 km, 2500 m, 5 km, 7500 m, 10 km, 15 km, 20 km and 30 km)	QGIS 2.18.16 + Place Syntax Tool Plug-In
4. Statistical Analysis		• Export QGIS attribute tables with network centrality values as excel worksheet • Multiply unweighted network centrality measures by road characteristics; segment length, speed limit and road capacity • Simple Linear Regression Analysis with unweighted and weighted network centrality measures • Multiple Regression Analysis with multiple independent variables* • Principal Component Analysis, PCA (how much is each variable contributing to explaining the traffic loads)*	Excel and Python or R statistical programming

*Methodology Steps for Further Research