Network Structure and Metropolitan Mobility

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August 1, 2010

Word Count: 5,320 words + 4 tables + 3 Figures = 5,320 + 4*250 + 3*250 = 7,070 words

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Abstract

The objective of this research is to develop quantitative measures that capture various aspects of underlying network structure, using aggregate level travel data from fifty metropolitan areas across the U.S. The influence of these measures on system performance is then tested using statistical regression models. The results corroborate that the quantitative measures of network structure affect the system performance. The results from this analysis can be used to develop network design guidelines that can be used to address current transportation problems.

Introduction

Changing urban form and network design to bring about change in travel behavior is a positive approach to improving transportation. This interest has extended to the fields of public policy and sustainability (Giuliano and Narayan, 2003).

A key element missing among the various modeling methodologies and approaches proposed by researchers is the explicit consideration of the structure of the actual transportation network. The transport system, specifically the street system, forms the primary structural element of any city. For example, as Marshall (2005) points out, the differences in modern cities such as New York or Los Angeles traces back to the transportation system in place during critical phases of growth for each city. Anas et al. (1998) argue that the spatial structure of modern cities can be traced back to the advances in transportation and communication infrastructure. An in-depth analysis of urban design and travel needs to explicitly consider the transportation network in terms of the structure, the actual layout of streets and routes.

Transportation planners acknowledge the importance of the transport system in influencing urban form. However most studies looking at the influence of urban form only consider a representation of easily measured metrics of the local transportation network (Cervero and Kockelman, 1997; Handy, 1992; Srinivasan, 2002). While these descriptive measures of roadway network structure are important, they don’t consider the arrangement and connectivity of nodes and links in the network and the impact of these aspects on the performance of the transportation system.

This research aims to continue the research interest in understanding travel behavior while explicitly accounting for the underlying street network structure, using aggregate level travel data from fifty metropolitan areas across the U.S. The argument presented here is that while the metropolitan transportation network need not be the only indicator of travel in a region, an understanding of the relationship between network architecture and travel is essential for the design of sustainable and efficient cities. The question of how travel behavior varies systematically with network structure is particularly important as network architecture is perhaps the slowest changing urban system. For that reason it is the most important to get right, as the design of the network persists for centuries and is difficult to adjust, much less optimize.

The goal is to quantify the street networks of fifty metropolitan areas and to understand the influence of these quantitative measures on two aspects of transportation (street) network performance, namely congestion and highway system usage. The rest of the paper is organized as follows: The next section briefly reviews relevant literature. This is followed by the section on modeling methodology, data sources, and the estimation of measures of roadway network structure. The model formulation and key
hypothesis are then identified. The statistical analyses conducted and the results follow in the next section. The paper concludes with key findings from the study and future extensions to the current research.

Literature Review

One of the earliest analysis of the relationship between accessibility and land use was conducted by Hansen (1959) as part of a study to develop a residential land use model. Horton and Reynolds (1971) provide a geographer’s perspective in their evaluation of the effects of urban spatial structure and accessibility on individual travel. An important contribution to the debate was made by Newman and Kenworthy (1989) who argued that the variation in transportation use between the U.S and other countries mainly reflects differences in land use patterns and transportation systems. This argument was countered by Gordon and Richardson (1989) and Gomez-Ibanez (1991) who criticized the theoretical and methodological foundations used in the study and the proposed policy recommendations. This debate has continued ever since (van de Coevering and Schwanen, 2006).

Bento et al. (2003) analyzed the influence of urban form and public transit supply on travel demand using national level travel survey data from 114 urbanized areas in the U.S. Giuliano and Narayan (2003) provide an international perspective by comparing travel diary data from the U.S and Great Britain. The results indicated that the differences in mobility patterns could be explained by the differences in both urban form and household income. Levine et al. (2009) related transportation accessibility outcomes to urban form using data from twenty four metropolitan areas in the U.S.

Muñiz and Galindo (2005) explored the role of urban form in influencing mobility and its ecological footprint, using commute data from 163 municipalities in Barcelona. Other metropolitan level comparisons include the role of monocentric and polycentric urban structures in influencing travel and its associated effects (ex. environmental costs, social costs etc) (Schwanen et al., 2001; Veneri, 2009).

A thorough review of the literature on urban form and travel patterns over twenty years has been compiled by (Stead, 2001). Krizek (2003) and Crane (2000) provide a similar review of the research highlighting the differences in modeling methodologies. None of the modeling methodologies used in travel behavior research however have explicitly considered the role of network design and its importance in influencing travel. The traditional interest in understanding transportation network structure has been limited to geographers who view the spatial nature of the transportation network as a vital input to the regional development (Haggett and Chorley, 1969; Rodrigue et al., 2006; Taaffe et al., 1996; Taaffe and Gauthier Jr., 1973).

Understanding network structure/topology

Kissling (1969) refers to network structure as a measure of the layout of the network and characteristics of individual elements. Xie and Levinson (2007) provides a similar definition of network topology as the arrangement and connectivity of the network. One of the earliest studies utilizing network measures to understand metropolitan settlement patterns was conducted by Borchert (1961). Kansky (1963) contributed by utilizing graph theory to develop a wide range of network measures to quantify the spatial
structure of transportation networks (railways and roadways). Kansky’s research was based on the pioneering study conducted by Garrison and Marble (1961), analyzing the relationship between the structure of transportation networks and characteristics of the area in which the networks are located. The interest in understanding network structure using graph theory tapered after the 1970s due to advances in computers and subsequent focus on developing complicated transportation models (Derrible and Kennedy, 2010).

Recent advances in GIS capabilities and related spatial analysis software has resulted in a revival of the interest in understanding the topological properties of complex networks. Yang et al. (2009) recently developed a method to identify and classify the spatial (grid-like) patterns in road networks with complicated junctions. Other advances include the use of fractal geometry and complex network theory to understand the patterns, structure and evolution of transportation networks (Jiang and Claramunt, 2004; Kim et al., 2003; Lu and Tang, 2004; Yan and Wang, 2009). Li and Shum (2001) developed accessibility measures based on graph theory to analyze the impacts of the National Trunk Highway System (NTHS) program in China. Barabasi and Bonabeau (2003) focused on scale-free networks in an attempt to understand the underlying principle governing extremely complex systems such as the world wide web.

Xie and Levinson (2007) investigated the potential application of proposed network measures in understanding and quantifying the structural attributes of complicated road networks. Three complementary measures of network structure: heterogeneity, connection patterns and continuity, were developed and tested on idealized test networks. The proposed network measures were later applied to the Swiss road networks to trace the changes in network characteristics over time (Erath et al., 2007).

These advances in network analysis have allowed researchers to focus on the relationship between network structure and travel. In a study evaluating pedestrian environments, Hess (1997) used quantitative measures of street network connectivity to explain the differences in pedestrian volumes between two neighborhoods (Wallingford and Crossroads) in the Seattle area. Dill (2004) presented results from a research project evaluating various measures of network connectivity for the purposes of increasing walking and biking. In a study looking at the journey to work, Levinson and El-Geneidy (2009) use circuity as a tool to better understand the relationship between residential location choice relative to work using data from the Twin Cities metropolitan region. The circuity measure has also been used at a national level using road networks from twenty six countries (Ballou et al., 2002).

In a recent study on network topology, Derrible and Kennedy (2009, 2010) use graph theory to characterize the network structure of 33 metro systems around the world. The analysis was then extended to study the relationship between network measures and transit ridership using data on a subsample of 19 subway systems. The results of the regression model show a strong relationship between the network measures and ridership indicating the importance of network design in attracting people to transit systems.

Our current paper aims to extend this interest in complex network analysis to road networks across the U.S and relate it the system performance and usage.
Modeling Methodology

The objective of this research is to understand the systematic variation in transportation system performance with measures of network structure, using data from the top fifty metropolitan areas across the U.S. The metropolitan areas were selected based on the year 2000 population data obtained from the U.S Census Bureau.

Data

The first step in this analysis is to obtain the relevant network and non-network data for the metropolitan areas considered in the study. The primary data for this empirical analysis comes from the following sources:

Street Networks

The street networks for the fifty metropolitan areas, used in this analysis, were extracted from the Census TIGER/line files. The Topologically Integrated Geographic Encoding and Referencing (TIGER) files, developed and maintained by the U.S Census Bureau, provide information on various features such as roads, railroads, rivers, as wells as legal and statistical geographic areas (U.S. Census Bureau, 2006). The extracted networks for the metropolitan areas were cleaned to include just the road features based on the Feature Class Codes (FCC) for the line segments provided in the Census TIGER/Line files.

Travel Data

The travel data is from the Texas Transportation Institute's Urban Mobility Report and provides information on the long-term congestion trends and the most recent congestion comparisons for 90 urban areas across the U.S. The data typically includes information on the:

- System usage - Vehicle miles traveled (VMT), annual passenger miles, unlinked transit passenger trips
- System supply - Highway lane miles by functional category
- Congestion measures - Annual hours of delay on the system, annual cost of congestion, congestion indexes like the Travel Time Index (TTI) and the Roadway Congestion Index (RCI).

The data on highway system usage was also supplemented by data from the Federal Highway Administration (FHWA)'s Highway Performance Monitoring System (HPMS) which is a national level continuing database that summarizes important statistics on the condition and performance of the highway system. The travel data for the year 2000 was extracted for the purpose of this analysis.

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1http://www.census.gov/geo/www/tiger/
2http://mobility.tamu.edu/ums/
3http://www.fhwa.dot.gov/policy/ohpi/hpms/abouthpms.cfm
Socio-Demographic Data

The socio-demographic data was obtained for the year 2000 from the U.S Census Bureau for the fifty metropolitan areas considered in the analysis. The socio-demographic variables are used as control variables in our analysis.

Estimation of Network Measures

The next step in the analysis is to estimate relevant network measures that capture the variations in network structure across the different metropolitan areas. This section details the indicators used to characterize the street network structure for the metropolitan areas in our analysis.

The measures used to quantify network structure across the different metropolitan areas are:

Treeness

This measure is based on the two basic structures of a planar transportation network: circuit and tree (Haggett and Chorley, 1969). A circuit is defined as a closed path, with no less than three links, that begins and ends at the same node. A tree is defined as a set of connected lines that do not form a complete circuit. A regional network distinguished by closed circuits is therefore called a circuit network while a network defined by a tree shaped structure is called a branching network. Refer to Xie and Levinson (2007) for a complete description of this measure.

Open source software was used to classify each segment in the street network as belonging to a branch network or a circuit network. This code was implemented on the street network of each metropolitan area. The street networks, as mentioned above, were obtained from the U.S Census Bureau.

The treeness for each street network was then estimated as:

\[ \phi_{\text{tree}} = \frac{L_t}{L_S} \]  

where,

- \( L_t \) = Length of street segments belonging to a branch network (km),
- \( L_S \) = Total length of the street network (km).

The associated circuitness is easily estimated as:

\[ \phi_{\text{circuit}} = 1 - \phi_{\text{tree}} \]

The treeness measures captures the differences in topology and connection patterns that exist among real-world street networks. Treeness can also be considered to be a measure of organization (in)efficiency. A map of the treeness estimated for each metropolitan area, is shown in Figure A-1.

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4Developed by Feng Xie, Metropolitan Washington Council of Governments (MWCOG)
5Code can be downloaded from http://nexus.umn.edu/Software/IdentifyingNetworkTopologies.zip
Completeness

This measure, as the name indicates, captures the level of completeness in the network using a link-node approach. This measure is similar to network connectivity measures, proposed earlier by Garrison and Marble (1961) and Kansky (1963). Road network are typically characterized by links and nodes. Links refer to the street segments while nodes refer to the intersection or junction of two or more links. Considering a road network with \( l \) links and \( n \) nodes, the network is said to be 100% complete if each node in the network is directly connected to each of the remaining nodes.

Figure 1 shows the relationship between the maximum number of direct connections in the network and the number of nodes in the network. Given a certain number of nodes (\( n \)) and assuming that the network is connected only by two-way links, the maximum number of links (\( l_{\text{max}} \)) in a network, is given by:

\[
l_{\text{max}} = n^2 - n
\]  

(3)

The number of links in a real world network is typically less than the maximum number of links and the completeness index used here captures this difference. The completeness of the street network in a metropolitan area is defined as:

\[
\phi_{\text{complete}} = \frac{l}{l_{\text{max}}} = \frac{l}{n^2 - n}
\]  

(4)

\( l \) refers to the number of links or street segments in the network and \( n \) refers to the number of intersections or nodes in the network.
The street networks obtained from the Census TIGER/line files were cleaned to ensure that the network contained only the relevant links and intersection or junction nodes. Shape nodes included in the TIGER/line files to ensure spatial correctness were removed as they do not represent actual intersection or junctions. The estimated completeness for each metropolitan area is plotted in Figure A-2.

**Street density**

Street Density ($\delta$) for each metropolitan area is estimated as:

$$\delta = \frac{L_R}{A}$$

where,

$L_R$ = Total roadway kilometers in the area,

$A$ = Size of the urban area ($km^2$)

The estimated measure has a unit of $1/km$. This measure differs from the completeness measure in that it provides a measure of the size of the actual network in comparison to the size of the urban area. The completeness on the other hand does not account for the urban area size and looks at the connectivity of the network using basic principles of graph theory. The street density can be considered to be a measure of the network intensity while the completeness is a measure of the efficiency in network connectivity. The correlation matrix presented at the end of this section confirms that the two measures are not correlated with each other.

**Percentage of freeways**

This measure is designed to capture the hierarchy in real-world street networks and is estimated for each metropolitan areas.

Specifically, the percentage of freeways is estimated as:

$$\%F = \frac{L_f}{L_R}$$

where,

$L_f$ = Total kilometers of freeways in the area,

$L_R$ = Total roadway kilometers in the area.

**Average Circuity**

Network circuity is defined as the ratio of the shortest path network distance to the Euclidean or straight line distance between an origin and destination. Levinson and El-Geneidy (2009) used a dataset of randomly selected, origins and destinations of actual trips to estimate circuity in their analysis of commute patterns and compared that to random OD points. The same methodology is implemented here, finding that circuity of actual home to work trips was lower than random OD points of the same trip length. Here we use circuity of random trips constrained to match actual trip length, which is highly correlated with (but higher than) actual commute circuity.

For each study area in our dataset, two samples were generated. The first sample consists of the origins and the second sample consists of the destinations. Similar to Levinson and El-Geneidy (2009), 200 randomly distributed origins and 1000 randomly
distributed destinations were generated using GIS. This provided 200*1000 OD pairs for each area resulting in a 200,000 OD matrix. The network distance and the euclidean distance were calculated for each of 200,000 OD pairs.

A subsample of OD pairs were selected out from the 200,000 random OD matrix in each study area by matching the network distance to the average commute trip length, provided in the 2001 National Household Travel Survey (NHTS)\(^6\). The average circuity for the subsample of OD pairs in each area was then estimated as:

\[ C = \frac{D_n}{D_e} \]  

where,  
\( C \) = Average circuity  
\( D_n \) = Sum of the network distance between all OD pairs in the subsample, \( D_e \) = Sum of the euclidean distance between all OD pairs in the subsample.

The circuity measure was estimated for 48 of the 50 study areas in our dataset. The circuity could not be estimated for two study areas, namely Richmond, VA and Birmingham, AL, due to the unavailability of commute data for these areas in the 2001 NHTS. Please refer to Levinson and El-Geneidy (2009) for a detailed explanation of the methodology.

The circuity measure is designed to capture the inefficiency in the network from the view point of a traveler.

**Accessibility**

Accessibility \( a \) was estimated for each study area using a combination of the above estimated circuity and the population density of the urbanized area, along with network speed. The estimation is as follows:

\[ a = A_t * D_{UA} \]  

where,  
\( A_t \) = Area \((km^2)\) that is covered in \( t \) minutes,  
\( t \) = any time contour, defined as 30 minutes (or 0.5 hour) in our analysis,  
\( D_{UA} \) = Urban area density \((persons/km^2)\).

\[ A_t = \pi * R_e^2 \]  

where,  
\( R_e^2 \) = Euclidean radius in \( km \), estimated as:

\[ R_e = S_e * t \]  

where,  
\( S_e \) = Euclidean speed in \( km/h \),  
\( t \) = 30 minutes as defined previously.

\[ S_e = S_n / C \]  

\(^6\)http://nhts.ornl.gov/
Table 1: Correlation of estimated measures

|                  | Treeness | Completeness | Street Density | Percentage of freeways | Circuity | Accessibility |
|------------------|----------|--------------|----------------|------------------------|----------|---------------|
| Treeness         | 1        |              |                |                        |          |               |
| Completeness     | -0.1340  | 1            |                |                        |          |               |
| Street Density   | -0.1800  | -0.0186      | 1              |                        |          |               |
| Percentage of freeway | 0.2082  | 0.1760       | -0.2761        | 1                      |          |               |
| Circuity         | 0.5042*  | -0.0368      | 0.2603         | 0.1581                 |          | 1             |
| Accessibility    | -0.3854* | 0.1145       | 0.4812*        | -0.2056                | -0.1401  | 1             |

* - Indicates significant at 95% confidence level

$S_n =$ Average network speed in km/h, provided by the Urban Mobility Report,  
$C =$ Average circuity, as estimated above.

The accessibility measure in this analysis measures the average number of people that can be reached in 30 minutes by automobile at uniform average metropolitan density. A review of accessibility shows many methods to estimating accessibility in the region (El-Geneidy and Levinson, 2006). The approach presented here is a simple measure estimated using the data available for all study areas and incorporates both the density aspect of urban areas and the structure of the street network. The accessibility measure was estimated for 48 of the 50 study areas due to the lack of appropriate circuity measures for two study areas.

A correlation matrix of the above estimated network measures is provided in Table 1. The lack of high correlation between any of the estimated measures of network structure in Table 1 confirms that the variables are measuring different aspects of network structure.

**Theory**

The basic research question addressed in this paper is: *Does network structure affect transportation system performance?*

$$P = f(N_S, E)$$  \hspace{1cm} (12)

where,  
$P =$ Performance of the system, measured here as congestion ($P_C$) and usage ($P_V$),  
$N_S =$ Measures of street network structure,  
$E =$ Exogenous control variables.

Road networks have an underlying structure. This structure is defined by the layout, arrangement and the connectivity of the individual network elements, the road segments and their intersections. The differences in network structure exist across networks and within networks. For example, the street network of Houston differs from the street network of Boston.

The differences in network structures translates to differences in network quality and efficiency. Efficiency and quality can be measured through network connectivity, mobility and scale. Travelers respond to these differences by altering their travel patterns...
to suit the underlying network, which results in differences in network performance.

Networks are complex and have many aspects. Each aspect of network structure affects network quality and efficiency differently. The measures of network structure estimated in our research are meant to capture these different aspects of network structure. A broad set of hypotheses formulated for the effect of measures of network structure on network performance are presented below.

The influence of network structure on travel performance is analyzed in this research using two models. The first model predicts the congestion in an urban area. The second model analyzes the relationship between the highway usage in an urban area and network structure. The model specifications and hypotheses are detailed below:

Model 1 - Dependent variable: Congestion ($P_C$)

Congestion refers to capacity utilization and is directly related to the cost of travel. Congestion occurs when the demand on the road system exceeds the capacity of the system over a period of time. Therefore,

$$P_C = \frac{D}{S}$$

(13)

where,

D = Demand on the transportation system,
S = Supply of the transportation system

$$D = f(p)$$

(14)

where,

p = Population of the area,

$$S = f(L_R, N_S)$$

(15)

where,

$L_R$ = Total roadway kilometers in the area and is represented as,

$$L_R = L_l + L_{nl}$$

(16)

where,

$L_l$ = Length of the local streets in the area (km),
$L_{nl}$ = Length of the non-local streets in the area (km),
$N_S$ = Measures of street network structure quality and quantity

The core hypotheses are:

- An increase in the demand, measured as population of the area ($p$), increases congestion, ceteris paribus.
- An increase in the supply of the system decreases congestion.

An increase in roadway kilometers ($L_R$) in the area decreases congestion
An increase in the circuitness ($1 - \phi_{tree}$) of the network decreases congestion.
Circuitness is a measure of network organizational efficiency.
Model 2- Dependent variable: System Usage - DVKT per capita ($P_V$)

$$P_V = f(P_C, N_S, a)$$ (17)

where,

$P_V$ = Daily vehicle kilometers traveled (DVKT) per capita on all the roadways in the urban area, obtained from HPMS data,

$P_C$ = Price of highway travel, measured by congestion,

$a$ = Accessibility.

The actual measures of network structure ($N_S$) that influence the network quantity and quality were identified based on our understanding of the transportation system and are elaborated below in the hypotheses section.

The core hypotheses are described below.

Price ($P_C$) of highway travel measured in congestion, using the Travel Time Index (ratio of congested to freeflow time) decreases the DVKT per capita. We posit that travelers respond to an increase in price by reducing travel.

Network structure ($N_S$) comprises several measures, and how they operate is not always straight-forward. On the one-hand improving efficiency lowers the network distance or travel time required to reach destinations, and thus for a given set of activities, reduces the required travel. On the other hand, reducing distance required for a given set of destinations may lead to induced demand, whereby lowering net cost of traveling on the network point-to-point leads people to making longer trips. It is anticipated that the efficiency for given trips will outweigh induced demand effects, but this is in the end an empirical question that cannot be resolved by theory. The hypotheses are listed below.

- An increase in the percentage of freeways ($\%F$), measuring the speed on the network, will increase DVKT. Higher hierarchy links such as freeways are usually faster and are more suited for longer travel.
- An increase in the street density ($\delta$) variable, representing the quantity or supply of the network increases the DVKT per capita. This is in line with the induced demand hypothesis, where increases to roadway capacity or supply encourages people to drive more by reducing the cost of travel.
- An increase in the completeness ($\phi_{complete}$) of the network, measuring the efficiency in network connectivity between the origins and destinations, decreases DVKT per capita.
- An increase in the circuitry ($C$), measuring the network inefficiency at the OD trip level, will increase the DVKT per capita. Higher circuity indicates greater inefficiency between OD pairs as travelers need to use more circuitous route (greater network distance) to reach their destination.

Finally, accessibility to population ($a$) measures the number of opportunities (in this case other people, which is highly correlated with access to employment and retail activities) that can be reached in a given time. The more opportunities available, the less need for longer distance travel, and thus the lower the system usage.
Analysis

The objective of this research is to develop quantitative measures of network structure and understand the influence of these measures on two aspects of system performance in an urban area. The first model analyzes the relationship between congestion in an area and the estimated measures of network structure. The second model analyzes the relationship between the system usage and the identified network measures. This section presents the two models estimated and elaborates on the results from the respective models. The models presented here were selected based on the best fit for the data.

Model 1

Model 1 uses the basic model of congestion defined previously to understand the relationship between network structure and congestion. The congestion in the urban area is given by the Travel Time Index (TTI), provided as part of the Urban Mobility Report. The TTI is a ratio that measures the travel time in the peak period to the travel time under free-flow conditions (Schrank and Lomax, 2009). A higher value of TTI indicates higher congestion. As explained in the Urban Mobility Report, “a TTI of 1.35 indicates that a trip that takes 20 minutes under free flow conditions takes 27 minutes in the peak period.”

The TTI in an urban area is used as a dependent variable in this model. Alternate formulations of the proposed models - using different combinations of the independent variables and different functional forms (ex. linear, translog etc.), were tested. The results of the log-log regression model (robust standard errors) are presented in Table 2.

Table 2: Model 1 - Predicting Congestion (TTI)

| Dependent variable (ln): Congestion (TTI) | Coef. | t  | Sig. |
|----------------------------------------|-------|----|------|
| Population, \( p \)                   | 1.33E-01 | 6.19 | ***  |
| Total length of local roads (km), \( L_l \) | -1.79E-02 | -0.57 |           |
| Total length of non-local roads (km), \( L_{nl} \) | -5.73E-02 | -1.99 | *   |
| Network treeness, \( \phi_{tree} \)    | 5.19E-02 | 2.10 | **   |
| Constant                               | -1.04E+00 | -6.13 | ***  |
| Number of observations                | 50     |     |      |
| Adj. R-squared                        | 0.5891 |     |      |

Natural log of all variables considered in the analysis

The results presented in Table 2 identify the factors that influence congestion. All independent variables perform as expected. Our hypothesis argued for an increase in congestion due to an increase in demand. This is confirmed by the positive and significant coefficient for the population variable. Both the supply variables, namely,
the total length of local roads and the total length of non-local roads have a negative influence on congestion as hypothesized. However the total length of local roads is not significant.

The result from this model, relevant to our analysis, is that the treeness in the roadway network has a positive and significant influence on congestion. This is in line with our hypothesis that a minimally connected tree network leads to congestion on the existing system due to the lack of travel options. The results show that network (in)efficiency, as captured by the treeness variable, affects system performance, after accounting for other non-network control variables such as population.

Model 2

This model tests the relationship between system usage in an area and the measures of network structure, after controlling for non-network measures. The simple model presented here in Table 3 predicts the system usage as a function of the population. The system usage is measured as the total DVKT in the area. This model has an extremely good fit with an $R^2$ of 0.9036. The model shows that the usage of the system is largely a function of the population. However the use of population to predict DVKT does not tell us anything about the other system variables that influence usage.

| Dependent variable (In): System usage (DVKT) | Coef. | t   | Sig. |
|---------------------------------------------|-------|-----|------|
| Population                                  | 8.88E-01 | 18.70  | *** |
| Constant                                    | 4.41E+00  | 12.60  | *** |
| Number of observations                      | 50     |      |      |
| Adj. R-squared                              | 0.9036 |      |      |

In order to get a better understanding of the system, we replace the absolute measure of DVKT by the relative measure of DVKT per capita.

Model 3

Table 4 presents two models of system usage using DVKT per capita as the dependent variable. As with the congestion model, various formulations of the model using different functional forms and different combinations of the independent variables were tested. Only two selected models are presented and elaborated here for brevity.

Both models predict DVKT per capita as a function of network and non-network variables. The difference between the two models lies in the non-network variables considered in the analysis. The first model, Model 3A, uses population density and the predicted congestion from Model 1 as explanatory variables in predicting system usage. Model 3B, on the other hand, replaces these variables with the measure of accessibility. Both models use the same measures of network structure: street density, percentage of freeways, completeness and circuity. Other common explanatory variables between the two models include auto mode share and median household income in the area.
The use of predicted congestion in Model 3A, rather than actual congestion is to account for the causality between network congestion and usage. The congestion in a region is a function of the system usage and the system usage in turn is a function of the congestion. The existence of this causality was confirmed by separate analyses including actual congestion measures (TTI, weighted average speed) in the models of system usage.

The results from both the models of system usage, presented in Table 4, confirms the influence of network structure on system usage. Focusing on the measures of network structure, the street density has a significant positive influence on DVKT per capita in both models, confirming our hypothesis that a larger supply of the street network of an urban area encourages more travel. The percentage of freeways in the area is also significant and positive, as hypothesized. Higher hierarchy links such as freeways are faster and are suited for longer travel. Hence an increase in the percentage of freeways in the area increase DVKT per capita. The coefficient for the completeness in the network, measuring the efficiency in network connectivity, is negative in both models but is significant only in Model 3A. An efficiently connected network reduces the DVKT by providing good connectivity between the origins and destinations in the region and bringing them closer, reducing the need for travel. The average trip circuity is significant and negative in Model 3B and while positive Model 3A. As noted in the theory section, the effects of network structure are complex, and proper interpretation, given the sensitivity of this variable to model specification, require further investigation. The results from both models confirm our theory that aspects of network structure influence the performance of the transportation system.

The socio-demographic measures of population density, auto mode share, median household income and accessibility in the urban area show the expected influence on DVKT per capita. On a side note, Model 3B with the inclusion of accessibility shows a much better model fit, confirmed by the higher $R^2$. The better model fit with the inclusion of accessibility shows that the estimated accessibility is a better combination of congestion and density than using these variables independently and linearly in the regression models. As El-Geneidy and Levinson (2006) point out, using measures of mobility or congestion to understand the land-use and transportation interaction is insufficient. Cities with the highest congestion might not be desirable places to live from a mobility (congestion) viewpoint but are still attractive to residents because of the opportunities that they provide.

**Elasticities**

The models presented here use the network measures as independent variables in predicting congestion and system usage in a region. Both the models presented here are log-log models and the elasticity estimates can therefore directly obtained from the respective model coefficients. Looking at the model results, we can say that a 1% increase in treeness of the roadway network increases the congestion in the area by 0.052%. Similarly a 1% increase in the completeness of a street network decreases the DVKT per capita by 0.20%. A 1% increase in street density increases the DVKT per capita by a range of 0.36% - 0.56% while a 1% increase in the percentage of freeways increases the DVKT per capita by a range of 0.22% - 0.35%.

The take-away from this paper is that the design of a roadway network affects the performance of the transportation system and a combination of network design
Table 4: Model 3 - Predicting System Usage (DVKT) per capita

| Independent variables (ln)          | Coef.     | t     | Sig. | Coef.     | t     | Sig. |
|------------------------------------|-----------|-------|------|-----------|-------|------|
| Predicted congestion               | -1.93E+00 | -2.44 | **   | NA        | NA    | NA   |
| Population density                 | -1.90E-01 | -1.36 |      | NA        | NA    | NA   |
| Median household income            | 4.13E-01  | 2.26  | **   | 2.86E-01  | 2.32  | **   |
| Auto mode share                    | 8.59E-01  | 2.12  | **   | 8.43E-01  | 3.21  | ***  |
| Accessibility to population        | NA        | NA    | NA   | -5.16E-01 | -8.34 | ***  |
| Street density                     | 3.59E-01  | 3.35  | ***  | 5.62E-01  | 9.63  | ***  |
| Percentage of freeways             | 2.19E-01  | 2.12  | **   | 3.52E-01  | 7.36  | ***  |
| Network completeness               | -2.02E-01 | -4.04 | ***  | -4.75E-02 | -1.22 |      |
| OD trip circuity                   | 7.62E-01  | 1.97  | *    | -6.48E-01 | -1.94 |      |
| Constant                            | -2.26E+00 | -0.95 |      | 6.28E+00  | 3.83  | ***  |

| Number of observations             | 48        |       |      | 48        |       |      |
| Adj. R-squared                     | 0.6835    |       |      | 0.8285    |       |      |

Natural log of all variables considered in the analysis

* p<0.10, ** p<0.05, *** p<0.01

measures can be used to bring about the desired changes in travel patterns. The measures of network structure need to be considered along with other urban form measures to reduce travel.

For example, consider a scenario with two areas with the same urban form in terms of population and employment density. We argue that, considering everything else to be the same, a small change in efficiency of network connectivity, i.e., completeness can have additional benefits of 0.20% reduction in DVKT per capita. There are other variables that affect travel in a region and this model is a simple representation of travel in a region. But the results show that network design can be one of the tools to bring about changes in travel. This understanding and application of network structure measures to network design is critical in the design of sustainable environments and urban forms and enhancements of existing systems.

Conclusions

The objective of this research to develop quantitative measures that capture various aspects of network structure, such as topology, connectivity, and heterogeneity that exist in road networks, using aggregate level travel data from fifty metropolitan areas across

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the U.S. The influence of these measures on system performance was then tested using two linear regression models. The first model analyzes the relationship between congestion and the estimated network measures. The second model analyzes relationship between the DVKT per capita and the network measures.

The results from both the models confirm that the quantitative measures of network structure affect the system performance, after accounting for independent control variables that are non-network based. However the influence of network design varies based on the aspect of travel that is being measured. The model predicting congestion shows the influence of network treeness while the model predicting DVKT per capita shows the influence of street density, completeness and the percentage of freeways in the urban area.

As mentioned previously, the measures of network structure used in this paper capture some aspects of network structure and design. Transportation networks are complex and are multi-faceted. Extensions to the paper involve developing additional measures that capture other aspects of network architecture.

The analysis presented in this paper is a cross-sectional comparison across regions for one specific year. But as (Marshall, 2005) and (Anas et al., 1998) point out, the current spatial structure of cities is based on the changes made to the transportation system in prior years. A good understanding of the influence of network structure on system performance needs to consider the temporal aspect.

The focus of this research is primarily on quantifying street networks but travel in an area is affected by other transportation modes. Derrible and Kennedy (2009)’s research on transit network design shows that key components of network design have significant impact on ridership and transit system performance. Hence as part of this analysis on metropolitan areas, it is planned to quantify the structure of transit networks and see how this affects certain aspects of the transportation system such as modal share.

The analysis conducted in this paper supplements previous efforts to understand the influence of network structure on travel decisions at a micro-level, using household travel survey data from two urban areas in Florida (Parthasarathi et al., 2009). It is hoped that the macro-level analysis conducted in this paper across metropolitan areas will provide a comprehensive understanding of the relationship between network structure and travel, which can be used to develop network design guidelines that can be used to address current transportation problems.

Acknowledgements

The authors would like to acknowledge Dr. Ahmed El-Geneidy, McGill University, for providing us the initial datasets for the study. The authors would like to thank Paul Anderson, University of Minnesota, for his invaluable assistance with the data collection efforts.
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Figures
Figure A-1: Estimated treeness by area

Sources: U.S Census Bureau [http://www.census.gov/geo/www/cob/tr2000.html](http://www.census.gov/geo/www/cob/tr2000.html).

ESRI [http://www.esri.com/data/free-data/index.html](http://www.esri.com/data/free-data/index.html)
Figure A-2: Estimated completeness by area

Sources: U.S Census Bureau http://www.census.gov/geo/www/cob/tr2000.html.
ESRI http://www.esri.com/data/free-data/index.html