Network Centrality Assessment (NCA) as an alternative approach to predict vehicular traffic volume: A case of Colombo, Sri Lanka.

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\textbf{Abstract:} This paper presents a robust, dynamic and simplified method to predict vehicular traffic volume in urban and regional geographies based on Network Centrality Assessment (NCA). The case study was conducted in Colombo, Sri Lanka. Study employed three types of graphs and three kinds of analysis methods to compute network centrality referring to four centrality parameters; for identifying the predictability of vehicular traffic volume. Findings stress that, the road segments graph based on geometrical analysis method and the natural roads graph based on topological analysis method is far better in predicting the vehicular traffic volume and it is more appropriate to consider the multiple influence from multiple centrality parameters predicting vehicle volumes rather than strict being into the single best parameter. Hence, study concludes that it is more appropriate to employ NCA considering the multiple influence from multiple centrality parameters based on geometrical and topological analysis methods in predicting vehicle volumes.

\textbf{Keywords:} Predication method, Traffic volume, Network analysis, Centrality

\textbf{1. INTRODUCTION}

How do people move in transport networks? Why do some transport corridors tend to be more attractive than other corridors? Is human travel behavior having an effect on traffic flow distribution in transport networks? These are some fundamental questions that face the practitioners and researchers in traffic and transport engineering and planning as well as in urban planning and design. Studies on traffic flow patterns have given an extensive attention to answer those questions in the past few years. This is because, understanding of traffic flow patterns guides traffic & transport engineers and urban planners to resolve many burning issues of society (Noulas, Scellato, Lambiotte, Pontil, & Mascolo, 2012). However, recent World Bank publication referring to developing countries mentioned that, “in practice, failures of traffic and transport policy having serious adverse effects in most countries and most commonly, the failure has taken the form of planning decisions which do not adequately account the demand of public and private sector” (Gwilliam, 2004). Many of the methods adopted for demand modeling are either too expensive or data-consuming tasks. TRL report published in Transport Research Laboratory 2004 (as cited in 2011) has emphasized that the applications of traditional transport modeling, which are commonly use in developing countries, is an expensive affair and inefficient method to understand traffic and transport demand (Chiaradia 2006 as cited in Paul, 2009). Further, recent national transport policies in developing countries in Asian (i.e. India, 2006; Sri Lanka, 2008) noted that, the virtual lack of a database on traffic and transport statistics and localized methods to model the demand have
severely constrained the ability to formulate sound traffic and transport plans and projects.

In this background, there is a need to employ alternative methods to estimate and predict traffic and transport demand which can efficiently work under above mentioned data and cost constraint situations in developing countries in Asia. In order to cater the above need, this study is focused on an emerging set of research literature which is developed based on the graph theory and recently employed in urban planning and design disciplines to explain human movement patterns. Amongst, Hillier and his colleagues (Hillier, 1999); (Hillier & Iida, 2005) has developed a method to explain human movement patterns in urban space under the notion of space syntax. Space syntax is a theory about space and human behavior as well as an analysis tool developed based on the graph theory and network centrality parameters. In space syntax, centrality is termed as ‘integration’ and mapped as a property topology of the space on an index of closeness or accessibility (Hillier, 1999) and it recognizes the fact that human movements are related to the level of integration of a given road network. In contrary to the Hillier’s approach, Jian & Jia (2011) argue that “the movement patterns in street networks are self-organized through the interaction between moving agents and the underlying street networks, and have little to do with agents’ cognition”. With respect to the centrality measures, they have further suggested that closeness centrality is not a good indicator for predicting traffic flow; “Even the local integration is far from the best indictor” (Jiang & Jia, 2011). Instead they propose some alternatives such as Google’s PageRank, its modified version - weighted PageRank-, Betweenness and Connectivity. Porta, Crucitti, and Latora (2006) have introduced an alternative application considering the street topology-Multiple Centrality Assessment (MCA)- that explains human movement patterns through computing the distance metrically instead of computing it topologically. The MCA application measures the level that a given location is ‘being central’ not only through the means of being close to all others (i.e. Closeness), but also through the means of being intermediary among others (i.e. Betweenness), being straight to all others (i.e. Straightness) and being critical for the efficiency of the system as a whole (Porta, Crucitti, & Latora, 2006) Further to this, Porta, Crucitti and Latora (2006) argue that, the movement networks could be studied through assessing Multiple Centralities instead of single-best-fit centrality measure. That was a root cause of recent literature that attempts to identify the centrality through multiple measures. “The structural and morphological properties of a road network, represented in topological or geographic metric measurements, are considered to be the key factors that shape dynamic urban traffic flow” (Jiang and Claramunt, 2004); Turner, 2007; Jiang and Liu, 2009; as cited in Gao, et al., 2013). Despite the differences in arguments all of the above studies have been focused on testing the applicability of centrality parameters to explain human movement patterns.

This paper attempts to constructively contribute in overcoming three limitations noted in emerging research in this domain related to traffic and transport engineering, and planning. First, many of those researches have referred to larger cities in Europe and Australia, with very limited reference to the medium-scale and small-scale cities in Asia which is emerging at a rapid rate (Munasinghe & Bandara, 2007); (Kishimoto, Kawasaki, Nagata, & Tanaka, 2007); (Munshi, Zuidgeest, & Brussel, 2009); (Hassan & Hoque, 2010). Second, the authors of this paper have noted that most of the available studies have been focused on pedestrian movements rather than vehicular traffic. Third, these research studies are developing on stand-alone platforms with limited attention to compare and contrast the applicability of different centrality parameters and analysis method. Addressing the above gaps, objective of this study is to evaluate the suitability of centrality parameters and different network centrality analysis methods to predict vehicular traffic volume in Colombo, Sri Lanka which is a medium-scale Asian city.
The rest of this paper is organized as follows. A short description of the concept of centrality in network and Network Centrality Assessment (NCA) is given in the second section. The third section introduces the study area and the dataset used in this research. Method of study is presented in section four. Section five includes relationship analysis between vehicular traffic volume index and network centrality index. Conclusion and recommendations for future studies presents in section six.

2. CENTRALITY AND NETWORK CENTRALITY ASSESSMENT (NCA)

The concept of centrality in networks can be traced back to the 19th century (Jordan, 1869 as cited in Holme, 2003). According to the work of Freeman (1979 as cited in Holme, 2003) many centrality measures are designed to capture different aspects of the centrality concept, which has been proposed within the study of social networks. Bavelas (1948 as cited in Fikel 1980) is considered as the first who realized that central individuals in a social network very often play a prominent role in the group, and similarly central locations in a physical network structure corresponds to power in terms of independence, influence a control on the others. In classic urban geography, the notion of centrality is generally defines in terms of attractiveness (Losch, 1952; Isard, 1956; Alonso, 1964; Herbert and Stevens, 1960 as cited in Cutini, 2001). Erdos and Renyi (1959) defined centrality measures as analytical methods developed based on ‘Graph Theory’; “centrality is relative importance of a vertex within the graph in terms of the degree of properties as number, distance, travel time, optimal path...”. According to the Freeman (1979) centrality is a measure of “the contribution of network position to the importance, influence and prominence of an actor in a network”. Hiller (1999) introduced the concept of centrality ‘as a process’ which “local road grid conditions are shown to be the key variable associated with the attractiveness of a local center in the sense that grid intensification functions to sustain circulatory of movement beneficial to the development of retail activity”. The concept of centrality applied in social networks has also been recently applied to study complex urban space and transportation networks (Holme, 2003; Porta, Crucitti, & Latora, 2006). Wilson (2000 as cited in Porta, 2007 et la.) stresses that though centrality defines under various terms, the idea is that some place nodes in a network are more important than others. Crucittiia, Latorab, and Marchioric(2004) highlight centrality as a fundamental concept in network analysis. While in the past the role and identity of central nodes were investigated, now the emphasis is more shifted towards the distribution of centrality values through all nodes. Accordingly, Network Centrality Assessment (NCA) can be defined as “an analytical method which has been developed based on the graph theory and applies to compute levels of centrality in a network based on a set of parameters”.

In order to compute the centrality of a network (e.g. transportation networks, utility networks), the first step is translating the real spatial structure or network into a graph. Hillier and Hanson (1984) introduced ‘axial-line’ based graph to represent urban space. According to the axial-line based graph representation employed by Hillier in space syntax, an axial line depicts the line of visibility from the origin, or the eye level, to the point of maximum vision. Thus, it termed as a visual network or graphical representation of the visibility lines. Further, an axial map of a city is defined as the least set of straight lines that pass through all the open space in the city (Batty & Carvalho, 2003).Turner (2007) and Dalton (2001) introduced a method to represent streets by a graph based on ‘axial segment’. Jiang and Clarumunt (2004); Jiang, Zhao, and Yin (2008); and Jiang and Liu (2009) employed two types of graphs called ‘Name Streets’ and ‘Natural Streets’ to predict human movements. Porta’s works on Mass Rapid Transits (MRT) networks in Australian Cites (2007 & 2008) have introduced a new approach for axial mapping that represent “points of transit stations as nodes and transit routes
which connect two stations as polylines”. In this map, links have been weighted based on impediment value (a function of travel time and service frequency between nodes). Further, street network has also been represented as primal or dual graph (Gao, Wang, Gao, & Liu, 2013). “In the primal representation each street intersection is transformed into a node, while a street segment is represented by an edge, where the length of segment could be measured as edge weight. In the dual representation, each street segment is transformed into a node, while a street intersection which may connects two or more than two street segments establish links among nodes where topological path steps as distance” (Gao, Wang, Gao, & Liu, 2013).

Methods of analysis in NCA are referred to a way of considering the shortest path between an origin and destination. In previous studies, three kinds of methods have been adopted in computing the level of centrality of a network based on a set of parameters which are metric, topological and geo-metrical. In metric and topological analysis methods, the shortest path is calculated by the distance where as in geo-metrical analysis method by the least angle in the graph. In metric analysis method, links (graph edges) are weighted by the metric distance between the two corresponding nodes (Jiang, 2008) while in geo-metric analysis method, by the geo-metric distance between two corresponding nodes. In topological analysis method, links are given a ‘unit weight’ (Porta, Crucitti, & Latora, 2006).

Network centrality has been measured by a range of parameters. Amongst, the works of Freeman (1979) and Hiller are widely referred in many of the literature. Freeman suggested three units of measures to capture the properties of networks centrality such as Degree Centrality (Dijkstra, 1959 as cited in Opsahl, 2010); Closeness Centrality (Sabidussi, 1966) and Betweenness centrality (Freeman, 1979) whereas Hiller introduced Connectivity, Integration and Choice. Despite the differences in calculations, the basic concepts of degree centrality, closeness centrality and betweenness centrality are somewhat similar to the connectivity, integration and choice respectively.

In this study, three types of graphs; axial line, axial segments (this will be referred as ‘road segments’ in rest of the paper) and natural roads are used to represent real-world road networks. Three kinds of analysis methods (i.e. metric, topological and geo-metrical) are employed to compute network centrality in the case study area referring to four centrality parameters (i.e. Connectivity, Global Integration Local Integration and Choice).

3. STUDY AREA AND DATA DESCRIPTION

Colombo Metropolitan Area (CMA) in Sri Lanka has been selected as the case study. CMA is one of the emerging urban agglomerations in South Asia with 5.8 million residential population and it accounts 30% of the country’s population (Department of Census & Statistics, 2012). The population density of the CMA is 3,699 persons per sq.km (Department of Census & Statistics, 2012). According to the JICA study (JICA, 2014) the great majority of industries, corporations and administrative institutions are located in CMA area which contributes more than 50% of country’s GDP. The overall gross trip production rate in the CMA is 1.87 per person. Around 38% of trips are made by private modes while 40% are made by buses and railway and the remaining trips are made by non-motorized modes. The number of trips per day in CMA is around 700,000 and 20% of these trips are made during the morning peak period. Average trip length is 6.2km by private mode, 10.2km by public mode and 2.2km by non-motorized mode. Seven national roads are radiated from the center (i.e. Colombo Fort Area) and connect major towns of the CMA as well as other main cities and towns in the country. Further, Baseline road connect north and south of the Colombo Municipal Council (CMC) area. The road density of CMC is 10.7% whereas 3.8% in CMA.
Data related to average daily vehicular traffic volume and road network were collected from secondary sources and stored in ArcGIS database. Accordingly, average daily vehicular traffic volume by road segment was taken as the input for vehicle traffic volume index and road network were used to prepare graphs. Table 1 gives brief description about the data.

<table>
<thead>
<tr>
<th>Data Type</th>
<th>Source</th>
<th>Year</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average daily vehicular traffic volume</td>
<td>Road Development Authority (RDA), Sri Lanka</td>
<td>2007</td>
<td>▪ Data has been collected from 24-hour automatic survey</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>▪ 266 data records were obtained along road links</td>
</tr>
<tr>
<td>Road network</td>
<td>Survey Department, Sri Lanka</td>
<td>2010</td>
<td>▪ Included information related to road name, road type and year of construction</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>▪ Polygon GIS layer: Road polygon</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>▪ Line GIS layer: Road centerline</td>
</tr>
</tbody>
</table>

![Figure 1. Study area and CMA (left) and Distribution of average daily vehicular traffic volume (right).](image)

4. METHODOLOGY

As stated earlier, the objective of this study is to evaluate suitability of centrality parameters and different analysis methods related to network centrality assessment to predict vehicular traffic volume. Hence, the study consisted of three main steps (refer figure 2).
The first was the preparation of Vehicular Traffic Volume Index. The second was the preparation of Network Centrality Index based on Network Centrality Assessment (NCA). The third was to investigate a possible relationship between the network centrality and actual vehicle traffic volumes.

NCA is the core of this study which aiming to compute the centrality of each road segments in the overall road network. Steps of NCA are introduced along with basic principle and some the basic concepts in section four.

4.1. Preparation of graphs

This study used three kinds of graphs which are Axial Lines, Road Segments and Natural Roads to represent road network. Figure 3 depicts a sample extracted from study area which represents total number of links by three types of graphs.

<table>
<thead>
<tr>
<th>Axial Lines</th>
<th>Road Segments</th>
<th>Natural Roads</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1" alt="Axial Lines" /></td>
<td><img src="image2" alt="Road Segments" /></td>
<td><img src="image3" alt="Natural Roads" /></td>
</tr>
<tr>
<td>No. of Link =11,286</td>
<td>No. of Link =34,861</td>
<td>No. of Link =2,323</td>
</tr>
</tbody>
</table>

Figure 3. Three kinds of graphs
(Note: Unique color has been given to symbolized the each links)

Hillier and Hanson (1984) have introduced the Axial Line based representation and it represents the longest visibility lines over the space or along the road. This study has used a GIS data layer of road polygons and converted it in to axial lines by using UCL Depth Map 10 software application (Refer figure 4). Accordingly this graph represents the unobstructed line of movement along the road (Hillier and Hanson, 1984).
Segments based graph representation has been introduced by Turner (2001) and Dalton (2001). This graph facilitates the angular (Geo-metric) analysis of the road network by considering the effect of turn angles at road intersections. Road segment graph is formed by chopping the original road center lines at each junction into smaller individual parts.

Next graph is Natural road and it represents roads which are naturally merged together with good continuity (Jiang & Liu, 2009). This study has used road segments graph prepared in previous step to create Natural road graph. Axwoman extension in ArcGIS software has been used to automatically generate Natural road graph by tracking the road segments within a 45 degree value of angle change limitation.
4.2. Analysis methods

This study used three kinds of analysis methods which are metric, topological and geo-metric (angular) and table 2 summarizes key features of those methods. The basic difference among the three analysis methods is the way of calculating the shortest-path.

Table 2. Methods of analysis

<table>
<thead>
<tr>
<th>Analysis</th>
<th>Metric</th>
<th>Topological</th>
<th>Geo-metric (Angular)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Diagram</td>
<td><img src="metric_diagram.png" alt="Metric diagram" /></td>
<td><img src="topological_diagram.png" alt="Topological diagram" /></td>
<td><img src="geo-metric_diagram.png" alt="Geo-metric diagram" /></td>
</tr>
<tr>
<td>Way of calculating the shortest path and distance</td>
<td><img src="distance_calculation.png" alt="Distance calculation" /></td>
<td><img src="distance_calculation_topological.png" alt="Distance calculation" /></td>
<td><img src="distance_calculation_geo-metric.png" alt="Distance calculation" /></td>
</tr>
<tr>
<td>Metric</td>
<td><img src="metric_method.png" alt="Based on 'shortest metric' distance between two points" /></td>
<td><img src="topological_method.png" alt="Based on 'fewest turns' between two points" /></td>
<td><img src="geo-metric_method.png" alt="Based on 'least angle change' between two points" /></td>
</tr>
<tr>
<td>How to calculate</td>
<td><a href="metric_formula.png">Distance formula</a></td>
<td><a href="topological_formula.png">Distance formula</a></td>
<td><a href="geo-metric_formula.png">Distance formula</a></td>
</tr>
<tr>
<td>Example</td>
<td>Distance = 5+7+10.6+5.7 = 28.3km</td>
<td>Distance = Total number of turns</td>
<td>Distance = 90/180 ×2 + 45/180 ×2</td>
</tr>
</tbody>
</table>

4.3. Centrality parameters

This study used three kinds of centrality parameters which are Connectivity, Integration (Global & Local) and Choice and table 3 summarizes the key features of those centrality parameters.

Table 3. Centrality parameters

<table>
<thead>
<tr>
<th>Centrality parameter</th>
<th>Way of calculation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Connectivity (C_i)</td>
<td>C_i = k</td>
<td>The level of C_i refers the number of lines to which the particular line is directly connected in the graph. Lines with high connectivity values are more connected than other lines and suppose to attract more traffic.</td>
</tr>
<tr>
<td></td>
<td>Where, k = number of direct connections (Hillie &amp; Iida, 2005)</td>
<td></td>
</tr>
<tr>
<td>Global Integration</td>
<td>GL_i = 1/ Σ_k d_k</td>
<td>Level of GL refers the extent that a given line closes to all other lines in the graph. Lines with high integration values are closer than other lines and suppose to attract more traffic.</td>
</tr>
<tr>
<td>(GL_i)</td>
<td>Where d_k refers to the shortest-path between line i and line k. (Hillie &amp; Iida, 2005)</td>
<td></td>
</tr>
<tr>
<td>Local Integration</td>
<td>This parameter is same as the global integration value but it is calculated for a smaller space (n=3 or 7..).</td>
<td>Level of LI refers the extent that a given line closes to all other lines in radius of 3 or 7 steps away from it. Lines with high local integration values are closer than other lines and suppose to attract more traffic from local areas (neighbourhoods).</td>
</tr>
<tr>
<td>(LI_i)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Choice (Ch_i)</td>
<td>Ch_i = Σ_i [d_{jk}(i) / d_{jk}]</td>
<td>Level of choice refers the extent a given link belongs to the shortest-path between any pairs of two links in the graph. Lines with high choice values are located central to the shortest path which links other pairs of two links and suppose to attract more traffic.</td>
</tr>
<tr>
<td></td>
<td>Where d_{jk} refers to the shortest path between line j and line k; d_{jk}(i) refers to the shortest containing line i between line j and line k (Hillie &amp; Iida, 2005)</td>
<td></td>
</tr>
</tbody>
</table>
4.4. Preparation network centrality index

Once the three types of graphs were prepared, level of centrality of each line was calculated based on the above mentioned centrality parameters. For that UCL Depth Map 10, Axwoman extension in ArcGIS and Pajek software applications were used and due to the limited functions of the software only five (out of nine) possible combinations were calculated.

<table>
<thead>
<tr>
<th>Type of graph</th>
<th>Metric</th>
<th>Topological</th>
<th>Geo-metric (Angular)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Axial lines</td>
<td>×</td>
<td>✓</td>
<td>×</td>
</tr>
<tr>
<td>Road segments</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Natural roads</td>
<td>×</td>
<td>✓</td>
<td>×</td>
</tr>
</tbody>
</table>

✓ Computed; × Not computed.

UCL Depth Map computation produced 20 types of outputs (5 combinations x 4 centrality parameters) result indicating the centrality values of links. Network Centrality Index was prepared from that in the ArcGIS platform.

5 ANALYSES: RELATIONSHIP BETWEEN VEHICULAR TRAFFIC VOLUME INDEX AND NETWORK CENTRALITY INDEX

5.1. Distribution of traffic volume and network centrality values

Traffic Volume Index comprised with 266 data records and it ranges between 108,021 and 726. Figure 7 demonstrated cumulative probability distribution of traffic volume. Accordingly, more than 60% of road segments have traffic volume less than the average value (i.e. 22,051) while less than 1% of road segments record very high traffic volume. This result implies that the distribution of traffic volume of the study region has characteristics of quasi-absence of dominant traffic corridors.

![Figure 7. Distribution of traffic volume index](image)

Network Centrality Index comprised of 18 variables and figures 8.a and 8.b. demonstrate power law distribution along with spatial distribution (8.c., 8.d. and 8.e.) of those variables. “Power law has been treated as a universal law, and has recently received a revival of research interests in an array of disciplines including for instance, physics, biology, sociology, and computer science” (Newman 2005 cited in Jiang, 2008). To examine power law distribution, this study plots the log-log plots where x-axis represents log centrality values,
and y-axis represents log cumulative probability.

Figure 8a. Power law distribution – Network centrality values.
Results indicate that Choice (refer figure 8.a. 4-8) and Global Integration (refer figure 8.a. 9-12, 8.b.1) centrality values exhibit very close relationship to the power law distribution followed by Local Integration and Connectivity. This finding indicates that study road network follow the scale free property of the network (Barabási & Albert, 1999) and in line to the findings of Carvalho and Penn (2004), Porta et al (2006) and Jiang (2009). However, this study able to make an additional contribution to previous research findings by examines the impact on power law distribution of the network according to different graphs and analysis methods. Results indicate that all three types of graphs and method of analysis are in line with power law. Accordingly, it can be concluded that there is nor or very limited impact on power law distribution based on different graphs and analysis methods compare to the types of centrality parameters.

Figure 8.c, Figure 8.d and Figure 8.e indicates the spatial distribution of network centrality values. The highest values are indicated in red colour and the lowest values are indicated in blue colour. Maps visualizing the choice and global integration centrality patterns according to the three analysis methods as shown in figure 8.c. Figure 8.d indicates maps visualizing the connectivity, choice, global integration and local integration centrality values based on types of graphs. Figure 8.e. shows spatial distribution of centrality values based on analysis methods. Visual comparison of those maps indicates that spatial distribution pattern of each centrality parameter based on different types of analysis methods and graphs are unique and have significant variation with each other.
<table>
<thead>
<tr>
<th>Methods of Analysis</th>
<th>Metric</th>
<th>Geo-metric</th>
<th>Topological</th>
</tr>
</thead>
<tbody>
<tr>
<td>Choice</td>
<td><img src="image1" alt="Choice Metric" /></td>
<td><img src="image2" alt="Choice Geo-metric" /></td>
<td><img src="image3" alt="Choice Topological" /></td>
</tr>
<tr>
<td>Global Integration</td>
<td><img src="image4" alt="Global Integration Metric" /></td>
<td><img src="image5" alt="Global Integration Geo-metric" /></td>
<td><img src="image6" alt="Global Integration Topological" /></td>
</tr>
</tbody>
</table>

Figure 8.c Spatial distribution of Choice and Global Integration centrality values based on methods of analysis.
<table>
<thead>
<tr>
<th>Connectivity</th>
<th>Choice</th>
<th>G. Integration</th>
<th>L. Integration</th>
</tr>
</thead>
<tbody>
<tr>
<td>Axial Lines</td>
<td><img src="image1.png" alt="Image" /></td>
<td><img src="image2.png" alt="Image" /></td>
<td><img src="image3.png" alt="Image" /></td>
</tr>
<tr>
<td>Road Segments</td>
<td><img src="image4.png" alt="Image" /></td>
<td><img src="image5.png" alt="Image" /></td>
<td><img src="image6.png" alt="Image" /></td>
</tr>
<tr>
<td>Natural Roads</td>
<td><img src="image7.png" alt="Image" /></td>
<td><img src="image8.png" alt="Image" /></td>
<td><img src="image9.png" alt="Image" /></td>
</tr>
</tbody>
</table>

Figure 8.d Spatial distribution of centrality values based on types of graphs.
<table>
<thead>
<tr>
<th>Metric</th>
<th>Connectivity</th>
<th>Choice</th>
<th>G. Integration</th>
<th>L. Integration</th>
</tr>
</thead>
<tbody>
<tr>
<td>Topological</td>
<td><img src="image1.png" alt="Image" /></td>
<td><img src="image2.png" alt="Image" /></td>
<td><img src="image3.png" alt="Image" /></td>
<td><img src="image4.png" alt="Image" /></td>
</tr>
<tr>
<td>Geo-metric</td>
<td><img src="image5.png" alt="Image" /></td>
<td><img src="image6.png" alt="Image" /></td>
<td><img src="image7.png" alt="Image" /></td>
<td><img src="image8.png" alt="Image" /></td>
</tr>
<tr>
<td>Metric</td>
<td><img src="image9.png" alt="Image" /></td>
<td><img src="image10.png" alt="Image" /></td>
<td><img src="image11.png" alt="Image" /></td>
<td><img src="image12.png" alt="Image" /></td>
</tr>
</tbody>
</table>

Figure 8.e. Spatial distribution of centrality values based on methods of analysis.
5.2. Correlation analysis

Bivariate Pearson correlation coefficient test in SPSS (Statistical Package for Social Science, 18th version) software was employed to find out the nature and the strength of a the relationship between traffic volume and network centrality. Table 5 illustrates summary result of correlation analysis.

Table 5. Summary result correlation analysis.

<table>
<thead>
<tr>
<th>Centrality Parameter</th>
<th>Type of graph</th>
<th>Method of analysis</th>
<th>r Value (Correlation Coefficient)</th>
<th>Rank according to the r value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Connectivity</td>
<td>Axial Lines</td>
<td>Topological</td>
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**Correlation is significant at the 0.01 level (2-tailed); N=266

In this inquiry, significant positive correlation between traffic volume and network centrality values were identified. That indicates the capability of NCA in predicting traffic volume. However, the level of coefficient of correlation is different by centrality parameters, type of graph as well as methods of analysis. In summary;

1. Road segment graph revealed a relatively higher value than those for the other two types. It can be concluded that, Road segment is the best type of graph followed by Natural Road and Axial Line graphs.

2. Geo-metric methods revealed a relatively higher value than those for other two methods. Accordingly Geo-metric analysis method is the best method followed by Topological and Metric.

3. It could also be seen that Choice centrality parameter seems to have the highest correlation with the correspondent traffic volume, followed by the global integration, local integration and connectivity.
5.3. Regression analysis

Forward multiple regression analysis was employed to predict the traffic volume using centrality values and to identify comparative impact of different levels of centrality on traffic volume. In other words, a quasi-hedonic model explaining the traffic volume values taking the following form was going to be created, tested, and analyzed. Forward linear regression is performed in this regard.

\[ \text{Traffic volume} = f(\text{Choice RoadSegment Geo-metric, Connectivity NaturalRoads Topological……...}) \]

(Table 6. Models Summary)

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<th>Model</th>
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<th>Adjusted R Square</th>
<th>Std. Error of the Estimate</th>
<th>Change Statistics</th>
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(Refer appendix-1 for details)

(Table 7. Coefficientsa)

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<th>Model</th>
<th>Unstandardized Coefficients</th>
<th>Std. Coeff.</th>
<th>t</th>
<th>Sig.</th>
<th>Collinearity Stat.</th>
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a. Dependent Variable: average daily traffic volume (Refer appendix-1 for details of other models)

Regression analysis indicated that the average daily traffic volume can be explained by using centrality parameters with more than 70% (R sq = 0.7) accuracy. Accordingly, influence of different centrality parameters on total daily traffic volume varies as follows.

- the level that road segment is located central (or intermediary) to the shortest paths (in terms of geo-metric distance) which links the road segments in the region (Choice_RoadSegment_Geo-Metric) by 54% (Beta = .543);

- the level that road segment is located near (in terms of topological distance) to the road segments in the surrounding area (3 km radius area) (Local Integration_Axial Line_Topological) by 20% (Beta = .199);

- the level that road segment is located near (in terms of topological distance) to the road segments in the region (Global Integration_Axial Line_Topological) by 20% (Beta = .201)
the level that road segment is directly connected to the other natural roads in the region by (Connectivity_Natural Street_Topological) 17% (Beta = .170)

Ratio between overall observed and predicted traffic values for study area is 67% (177/267) but this values is significantly high (117/144=83%) in center (10km radius area) of the study area compare to the same for edge (9/37=24%) of the study area. This is because of the error occurs due to edge effect which can be commonly observed in spatial network analysis (Turner, 2007) but study strongly recommend to investigate this effect for different centrality parameter and methods of analysis and further, possible solution to overcome that.

6. CONCLUSION AND RECOMMENDATIONS

The study was carried out with the objective of evaluating the suitability of centrality parameters and different network centrality analysis methods to predict vehicular traffic volume in urban and regional geographies, therefore, the case study was conducted in Colombo Metropolitan Region, Sri Lanka. Accordingly, this study employed three types of graphs and three kinds of analysis methods to compute network centrality in the case study area referring to four centrality parameters; for identifying the predictability of vehicular traffic volume. Results revealed from the above mentioned analysis can be summarized into three points as follows. First, all three representations i.e. axial lines, road segments and natural roads have exhibited small-world and scale-free properties. Second, the road segments graph based on geo-metric analysis method and the natural roads graph based on topological analysis method have been far better in predicting the vehicular traffic volume in comparison to the other combinations. These two points have been emphasized in the works of Turner (2007) as well as Hillier and Iida (2005). They have further interpreted that human beings perceive the space mostly from geometrical and topological views rather than metric distance, therefore, angular (referred as ‘geo-metrical’ in this study) and topological analysis methods have better correlations to human movements (referred as ‘vehicular movements’ in this study). Third, as many other authors (Puzis, et la. 2011; Galafassi & Bazzan, 2014) agreed, ‘choice’ which is computed based on geo-metric analysis method has significantly influenced in predicting traffic volume. However, findings of this study stress that, the ‘global integration’, ‘local integration’ and ‘connectivity’ computed based on topological analysis method also have a significant influence on traffic volume. Hence, it is more appropriate to consider the multiple influence from multiple centrality parameters based on geo-metric and topological analysis methods in predicting vehicle volumes rather than strict into the single best parameter.

The methods demonstrated in this research offer a promise for transport engineering and planning applications in developing countries in Asia that it is urgently called for. On one hand this research has contributed to develop a robust and dynamic tool that can be employed with a more passive involvement where engineers, planners can identify and predict the traffic volume trends, and devise suitable strategies to overcome existing problems. Further, this is capable of making an active interference, where the whole area can be remodeled with a few carefully identified strategic projects (road networks) and steer the traffic flow trends in the area towards more desirable directions, deviating from ongoing trends. On other hand, this is a constructive contribution for emerging literature in spatial analysis applications of network centrality representation, analysis methods and parameters in predicting vehicular traffic volume. Future studies can further contributed to develop NCA through unbundling the traffic volume by types of vehicles and incorporating the route choices of vehicle users.
### APPENDICES - 1

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a. Dependent Variable: average daily traffic volume

### REFERENCES


