

Provided for non-commercial research and education use.
Not for reproduction, distribution or commercial use.



(This is a sample cover image for this issue. The actual cover is not yet available at this time.)

This article appeared in a journal published by Elsevier. The attached copy is furnished to the author for internal non-commercial research and education use, including for instruction at the authors institution and sharing with colleagues.

Other uses, including reproduction and distribution, or selling or licensing copies, or posting to personal, institutional or third party websites are prohibited.

In most cases authors are permitted to post their version of the article (e.g. in Word or Tex form) to their personal website or institutional repository. Authors requiring further information regarding Elsevier's archiving and manuscript policies are encouraged to visit:

<http://www.elsevier.com/copyright>

Contents lists available at [SciVerse ScienceDirect](#)

Transportation Research Part C

journal homepage: www.elsevier.com/locate/trc

A new street connectivity indicator to predict performance for feeder transit services



Shailesh Chandra¹, Luca Quadrifoglio*

Zachry Department of Civil Engineering, Texas A&M University, College Station, TX 77843-3136, United States

ARTICLE INFO

Article history:

Received 16 March 2012

Received in revised form 8 February 2013

Accepted 8 February 2013

Keywords:

Connectivity index

Feeder transit

Livability

Street network

ABSTRACT

This paper defines a novel street Connectivity Indicator (C.I.) to predict transit performance by identifying the role that street network connectivity plays in influencing the service quality of demand responsive feeder transit services. This new C.I. definition is dependent upon the expected shortest path between any two nodes in the network, includes spatial features and transit demand distribution information and is easy to calculate for any given service area. Simulation analyses over a range of networks have been conducted to validate the new definition. Results show a desirable monotonic relationship between transit performance and the proposed C.I., whose values are directly proportional and therefore good predictors of the transit performance, outperforming other available indicators, typically used by planners.

© 2013 Elsevier Ltd. All rights reserved.

1. Introduction

In recent times, public transit systems in the United States are facing stiff competition with private car usage. This problem has been recently echoed by the Federal Transit Administration (FTA) which recognized lack of first/last mile connectivity as preventing many potential passengers from using the main transit such as bus transit, and light rail (Mattice, 2012). The problem is particularly relevant in the context of first/last leg of the passenger travel- from a major transfer point or transport hub to the final destination (popularly known as “the first/last mile” access or connectivity). Policies which encourage the desired reduction of Vehicle Miles Traveled (VMT), reduction of greenhouse gases and even an increase of “livability” depend on solutions to the issue of first/last mile access to transit and multi-modal solutions. Thus, public transportation agencies must continue to explore and evaluate innovative ways of providing safe, convenient and efficient public transportation options to properly address the issue and improve the performance of their services.

It is generally difficult to identify a unique definition of performance of a transit system as priorities differ among stakeholders. Several authors have used measures such as passenger cost, passengers per vehicle hour, vehicle miles per operator, cost per vehicle mile, cost per vehicle hour, the ratio of cost to fare box revenue and fleet fuel efficiency for the urban public transit (Gleason and Barnum, 1982; Fielding et al., 1985; Badami and Haider, 2007; Quadrifoglio and Li, 2009). However, all seem to agree that transit performance can generally be identified as a combination of operating costs (roughly directly proportional to the traveled miles) and service quality, which can be expressed (for the most part) as passengers’ disutility: a weighted sum of expected waiting time, expected in-vehicle travel time and walking time (Chandra et al., 2011). Many other factors are certainly important, but generally considered less significant.

* Corresponding author. Tel.: +1 979 458 4171; fax: +1 979 845 6481.

E-mail addresses: chandrashailsh@gmail.com (S. Chandra), quadrifo@tamu.edu (L. Quadrifoglio).

¹ Tel.: +1 979 324 4792; fax: +1 979 845 6481.

Feeder transit services have been identified as one of the possible solutions to provide the ultimate first/last mile access for passengers, especially those residing in the residential areas. Many of these services operate in a demand responsive fashion in these residential areas (Koffman, 2004; Potts et al., 2010) and their performance is dependent on factors such as drivers experience, stop frequencies, shuttle types, and demand at every stop. However, one of the basic factors on which the feeder performance depends is the street network design and its connectivity, as vehicles are potentially required to reach any point in the service area to serve the demand. It is fair to say that, with all other factors being equal or comparable, connectivity becomes an important measure of demand responsive performance. Intuitively, the higher the network connectivity, the faster and more efficiently vehicles are able to serve customers and the better the feeder transit performance. Therefore, a relationship between the road network design (and its connectivity) and the transit performance would be very desirable to have for properly planning and enhancing transportation mobility in the residential areas. However, it is not trivial to describe or estimate this relationship. Current connectivity measures are not sufficiently accurate nor linked to transit performance, as it will be shown later in this paper.

The primary purpose of a street network system is to connect spatially separated places and provide movements from one place to another. The nature of these connections varies depending on the structure and design of the street network system from being one to many, direct to indirect or even divided among the kinds of connections to support different modes of travel. Qualitatively, these connections are expressed as the “connectivity” of the street network and influence the accessibility of potential destinations in a community. Connectivity has important implications as its quality influences the efficiency of public transportation, travel choices, emergency access and adds to the ‘livability’ of a community.

There are a number of attempts from researchers and practitioners to identify a good way to properly measure street connectivity with ‘connectivity indices or indicators’. Block length, block size and block densities are used as some of the ways to measure street connectivity (Handy et al., 2003; Frank et al., 2000; Cervero and Kockelman, 1997). But the requirements for the block length, size or density is only restricted to pedestrian and bicycle connections. Planners extensively use a ‘connectivity index’ defined as the ratio of number of links or edges (usually defined as the segment between two nodes or intersections) to the number of intersections (Dill (2004)). But the connectivity index defined using this ratio does not incorporate the link length information which intuitively affects connectivity. It is also quite easy to visualize that with the connectivity index definition above, two different street systems could have the same values of connectivity index depending on the way street link segments are constructed (Steiner and Butler, 2012). For example, there are four links and four nodes each in Plan A and Plan B of Fig. 1 with equal connectivity index value of unity.

Peponis et al. (2007, 2008) introduced the concepts of ‘reach’ and ‘directional distance’ as the measure of connectivity applicable to GIS-based representations of street networks. The metric ‘reach’ denoted by $R_v(P_i, \mu)$ of a point P_i (as the origin) is defined according to a metric threshold μ as the length of the road segments and fractions of road segments covered by the union of all paths for which the road segment of length ‘s’ is less than or equal to the threshold. The ‘directional distance’ denoted by $R_w(P_i, \delta, \mu, \alpha, r)$ of a point P_i is defined according to a directional threshold δ and a metric threshold μ as the length of all road segments and fractions of road segments which are no more than μ metric distance, and no more than δ directional distance, away from P_i , subject to a threshold angle α and a ratio r for defining very small line segments. However, looking closely at these measures of connectivity one can notice that they lack a closed form expression for defining the connectivity index for any general network. The Gamma index (defined in detail later under the Section 3). Other connectivity indicators that exists in Kansky (1963) is particularly useful in quantifying connectivity for a particular street network but does not include provisions for ridership demands or any passenger utility. Derrible and Kennedy (2009, 2010a, 2010b) studied the metro transit network system as graphs and in some sense there was a link between the connectivity and transit performance. However, metro rails have fixed tracks that they follow as a travel constraint and hence, do not bear very close resemblance to flexibility of other modes of transit which use streets.

The purpose of this study is to identify and test a new connectivity indicator, simply defined, easily computable and properly able to capture the relationship between connectivity and feeder transit performance. We are revising and expanding the definition of the ‘connectivity indicator’ in Lam and Schuler (1982) which depends on certain number of given travel times between demand points. However, neither the street network layout nor the passenger demand density distribution was taken into account.

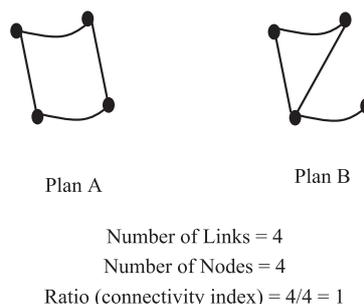


Fig. 1. Same connectivity index values for two different street plans.

2. Methodology

We consider a residential area served by an on-demand feeder bus service providing residents with transportation from/to their home to/from a major transit terminal. Passengers are able to book their rides by means of an internet/phone service. One or more ‘on-demand bus-stop’ node is assigned to each link of the road network. The maximum distance from any home to its closest on-demand stop is within the recommended walking capacity of the passengers which is usually 5 min of walk or approximately 1200 feet (O’Sullivan and Morrall, 1996). Assigning ‘on-demand bus-stop’ nodes helps both the bus operators and the passengers in serving at designated points along the cross street link when there are multiple requests made for service at that link. The on-demand nodes bus stops are not placed at the intersections. This is because mid-block bus stops are preferred for design as they minimize sight distance problems for the pedestrians and also help create less pedestrian congestion at the passenger waiting areas (Fitzpatrick et al., 1996). Demand could arise anywhere within the service area following some spatial/temporal distributions and is assumed to be assigned to the closest stop (see Fig. 2). The overall service time is reduced when there are multiple requests made for service at that link. The shuttle departs from the terminal at pre-set intervals. Immediately before the beginning of each roundtrip, customers’ service sequence is scheduled by some algorithm, so the route is constructed and the passengers served.

We aim to define a new Connectivity Indicator (C.I.) as a good predictor of the on-demand transit performance, which is composed by a weighed combination of operator’s objective (lesser total distance traveled) and level of service (shorter in-vehicle riding time and waiting time, assuming negligible walking time). Intuitively, all these terms are dependent on how fast the shuttle is able to serve customers.

The expected in-vehicle riding time (denoted by $E(T_{rd})$) and waiting time (denoted by $E(T_{wt})$) for a feeder transit service can be related to the cycle length (denoted by C) using the following equations (Quadrioglio and Li, 2009),

$$E(T_{rd}) = \frac{C}{2}, \tag{1}$$

$$E(T_{wt}) = (1 + \alpha) \frac{C}{2}, \tag{2}$$

where α is the portion of passengers going from home to terminal and $1 - \alpha$ the portion traveling from terminal to home.

In a given service cycle, a given set of on-demand nodes, say n , is scheduled for service (starting at the terminal denoted by $i = 0$ and returning back at the same terminal $i = n + 1$) and the total distance traveled is $D = \sum_{i=0}^n d_{i,i+1}$, where, $d_{i,i+1}$ is the shortest path between any two consecutive stops i and $i + 1$. Thus, the cycle length C is expressed as

$$C = \left(\frac{D}{v} + nt \right), \tag{3}$$

where t is the average dwell time spent at each stop and v is the average speed of the shuttle.

If N is total number of potential on-demand stops within the service area (with n being a subset of N), the sum of all the shortest paths among all potential N nodes, denoted by T , is given by,

$$T = \sum_{i=1}^N \sum_{j=1, j \neq i}^N d_{ij}, \tag{4}$$

It can be easily seen that the total traveled distance, D , is a fraction f of T (expressed as, $D = fT$), where this fraction ‘ f ’ will be different every cycle.

The operator objective (total distance traveled) of the transit performance is obviously directly proportional to D and thus T . The level of service components are too, in fact, by using Eqs. (1)–(3) and knowing that $D = fT$,

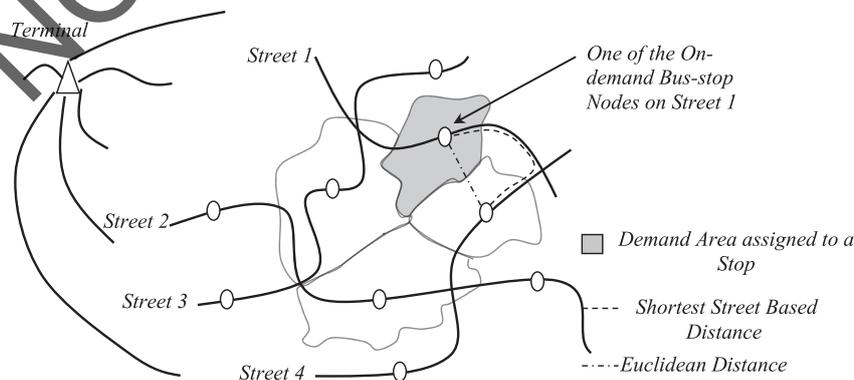


Fig. 2. On-demand bus stop nodes on cross street links.

$$E(T_{rd}) = \frac{1}{2} \left(\frac{fT}{v} + nt \right) \tag{5}$$

$$E(T_{wt}) = \frac{(1 + \alpha)}{2} \left(\frac{fT}{v} + nt \right); \tag{6}$$

Both the expressions for average riding time ($E(T_{rd})$) and average waiting time ($E(T_{wt})$) in (5) and (6) are both directly proportional to T .

Hence, a desirable Connectivity Indicator (C.I.) of a given network should logically also be proportional to T to be a good predictor of the transit performance.

2.1. Expected shortest path

When comparing different network configurations within a given service area for planning purposes, the simple use of T as C.I. would be good only if N is a constant among all options. However, it would be desirable to define a C.I. as general as possible and not necessarily dependent only on N . Different network options might in fact have more or less on-demand stops and this should not solely influence the transit performance estimation or prediction. Thus, we need to include other factors (besides the dependency from N) that influence performance, which is easily done by defining the average (expected) shortest path (denoted by S_a) that directly impacts C.I. If demand is assumed to be distributed uniformly among all the stops, then it can be easily seen that S_a is given by

$$S_a = T/[N(N - 1)]. \tag{7}$$

It is fair to say that uniformly distributed demand or population among all stops could be possible. In such cases, with egalitarian distribution of streets having sufficient number of stops and each nearest stop at some standard walking distance, the distances between stops will be a good way to measure C.I. However, in a more general case, demand might be unevenly distributed over the stops, so that some stops and the associated links to these stops are more likely to be visited by the shuttle during service than the others. Our C.I. definition takes into account the demand distribution dimension in addition to the network topology. The links and stops are therefore more critical than others for the overall transit performance. As an intuitive example, links connecting stops relatively far from the others but with little demands should not be considered as important as links connecting pairs of nodes with higher demands. Let A be the demand rate in the considered service area and let λ_i be the demand rate at the on-demand stop i (simply written as $A = \sum_{i=1}^N \lambda_i$, i.e. summation of all demand rates over N nodes). The likelihood for a pair of nodes i and j to be consecutive in a cycle (and the shortest path d_{ij} between them to be actually driven by the vehicle) is proportional to the product of their demand rate λ_i and λ_j . We can therefore express the expected shortest path between any two nodes in a network as

$$S = \frac{1}{A} \sum_i \left(\lambda_i \frac{\sum_j \lambda_j d_{ij}}{A - \lambda_i} \right), \quad \forall i, j \in \{1, 2, \dots, N\}, j \neq i, \tag{8}$$

which reduces to (7) for uniform demand. Thus, a good C.I. taking into account spatial demand distribution should be related to (8).

The uniform distribution of demand does not ensure that every on-demand node gets the same 'demand rate' (i.e. λ). The assumption is that if the demand is spatially uniform distributed over the area, the demand rate that each node receives becomes proportional to the area surrounding the node. Thus, when the node distribution is not uniform across the service area, each node gets a different share of demand rate. Thus, formula (7) is only used to show the validity of formula (8) for an extreme case result when all the demand rates are assumed to be 'equal' in value for the nodes.

2.2. Ideal network

The purpose of this section is to define an ideal network with "perfect" connectivity, which would allow an on-demand feeder transit service to achieve the best possible performance and hence, would be superior to any other real street network, under the uniformly distributed demand assumption. Theoretically, in a given area of length L and width W , the smallest possible average shortest path distance (denoted by S_{min}) is calculated by assuming Euclidean paths among all pair of points is given by Gaboune et al. (1993):

$$S_{min} = \frac{\sqrt{L^2 + W^2}}{3} + \frac{L^2}{6W} \ln \left(\frac{W + \sqrt{L^2 + W^2}}{L} \right) + \frac{W^2}{6L} \ln \left(\frac{L + \sqrt{L^2 + W^2}}{W} \right) + \frac{L^5 + W^5 - \sqrt{(L^2 + W^2)^5}}{15L^2W^2}. \tag{9}$$

The above expression in (9) will never be practically possible, as no real network can achieve it. A more realistic, yet still ideal, computation for S_{min} would consider rectilinear paths among demand points. Studies show that grid street patterns with relatively short block lengths are preferred for better connectivity as they provide plenty of route options for trips if covered by walking, transit or by using a private vehicle (Kostof and Tobias, 1991). It is in fact intuitive and accepted that maximum transit performance is reached as this layout provides multiple route options. Many residential street patterns

follow the grid-form of street networks. An example of a grid street pattern is shown in Fig. 3 below from the town of Hempstead (with block length $s \approx 350$ feet), a residential town fifty miles northwest of downtown Houston, TX, and there are several such grid networks as examples all around the cities and towns in the US.

Assuming an ideal infinitely dense grid network, the term S_{\min} would more simply be expressed using Gaboune et al. (1993) by S_{\min}^u as,

$$S_{\min}^u = (L + W)/3, \tag{10}$$

which is, of course, higher with respect to (9).

More rigorous values for S_{\min} might be calculated, taking into account actual constraints, such as, for example, the minimum allowable block length s , which would cause the grid not to be infinitely dense and S_{\min} to increase, but would not be easy to compute.

The purpose of defining S_{\min} or S_{\min}^u (computed with (9) or (10), respectively), allows us to have a value for it for an ideal network with “perfect” connectivity. Any other network serving the same area would have $S > S_{\min}$ (or, $S > S_{\min}^u$).

2.3. Connectivity indicator

In order to have the C.I. directly (not inversely) proportional to on-demand transit performance and to cause an ideal C.I. identifying a “perfect connectivity” to be equal to 1 (as most indicators are defined), we finally define it as follows,

$$\text{Connectivity Indicator(C.I.)} = S_{\min}/S = \frac{\frac{\sqrt{L^2+W^2}}{3} + \frac{L^2}{6W} \ln\left(\frac{W+\sqrt{L^2+W^2}}{L}\right) + \frac{W^2}{6L} \ln\left(\frac{L+\sqrt{L^2+W^2}}{W}\right) + \frac{L^5+W^5}{15L^2W^2} \sqrt{(L^2+W^2)^5}}{\frac{1}{\lambda} \sum_i \left(\frac{\lambda_i d_{ij}}{\lambda - \lambda_i} \right)} \tag{11}$$

where L and W are the length and width, respectively, of the area which encloses the street system. Recall that λ_i is the demand rate at the on-demand stop i with $\lambda = \sum_{i=1}^N \lambda_i$ (i.e. summation of demand rates of all nodes from $i = 1$ to $i = N$) and d_{ij} is the shortest street-based path between nodes i and j . An example calculation for the indicator is included in the Appendix A for reference.

In other words, the connectivity indicator proposed in (11) for evaluation of DRT performance can be simply defined as the ratio of a standard distance constant to the effective expected distance between stops/nodes for a given network. The standard distance constant in the numerator of (11), S_{\min} , is the ‘minimum’ possible average distance among stops located on a given network. This is different from the effective expected or average distance (S) in the denominator of (11) which is completely dependent on the actual proximity of two stops/nodes on the same network. This definition ensures that ideal networks with “perfect” connectivity would have a C.I. equal to 1. Any real network with shortest paths calculated over actual available links would have C.I. less than or equal to 1.

We’d like to emphasize that identifying a precise absolute S_{\min} instead of the ones proposed above would not be a crucial step for the purpose of improving this study, as S_{\min} behaves as a constant multiplier within the C.I. definition. Its value is important to evaluate how well a given network is doing with respect to a defined ideal case, but would not be crucial in comparing multiple network options among each other, as all would have S_{\min} .

The proposed C.I. in (11) is very easy to calculate for any street network system and should be a very good predictor of the on-demand transit performance: intuitively, the higher the C.I. the better the transit performance. The proposed connectivity



Fig. 3. A grid section of the street network system of the town of Hempstead, TX. Source: Google Earth.

indicator in (11) is also robust enough for analysis of DRT systems operating in a downtown area as well. For this the only change would be to replace the distance (d_{ij}) term in the connectivity indicator of (11) with travel times between on-demand nodes. This would make the indicator applicable for use for any given street system whether in downtown, residential or a mix. The problem, however, would be in obtaining travel times or speed of the DRT shuttle between nodes which would make the indicator not so simple to use as in its present form.

3. Other connectivity indicators

Most common currently available indicators to measure connectivity that we already mentioned earlier are better summarized below. We will compare our proposed C.I. against these two in the next section for validation purposes.

3.1. Gamma index

Graph theory measure of network connectivity for planar graphs, known as the *Gamma index*, is expressed as $\frac{e}{v-2}$, where v is the number of vertices (or nodes) present in the network and e is the number of edges (or links) connecting the vertices. A node is formed due to an intersection of two or more links in the network. The end point of a free link such as that of cul-de-sac or a dead end is automatically counted as a node. Going by the definition of Gamma index, the higher the Gamma index the greater connected should the network be and vice versa.

3.2. Transportation planning indicator

The connectivity index in transportation planning is measured as the ratio of the total number of links to the total number of intersections in the network. For this connectivity measure used in planning, the higher the index value the greater the connectivity of the network. Intuitively, the link to node ratios should always be less than 1, however, a simple example (see Fig. 4) taken from Dill (2004) clearly shows that this ratio can be greater than 1 (number of links = 9, number of nodes = 8, Ratio = $9/8 = 1.13$). Similarly, there can be several other networks that might exist that could have link-to-node ratio greater than unity.

4. Simulation results and discussions

The aim of the following simulation analyses is to demonstrate the robustness and the applicability of proposed C.I. (Eq. (11)) for some reasonably assumed data sets and parameters. We resorted to simulation to demonstrate the robustness of the proposed indicator since passenger demand distribution for DRT is random in nature and simulation is often the most preferred approach in assessing performances of such similar transit services that are demand responsive (see Fu (2002), Quadrifoglio et al. (2007) and Gupta et al. (2010)). An on-demand feeder service running for a range of cycle lengths varying from 7.5 to 40 min and serving a demand of $\eta = 300$ passenger per day within a rectangular area of $L = 2400$ feet, $W = 2100$ feet and $s = 350$ feet (minimum block size), is assumed to be put in operation in ten different street network patterns from different parts of Palm City, FL and Hempstead, TX (see Fig. 5).

The proposed indicator is constructed in a way such that any other appropriate value of distance (s) between on-demand nodes selected by a user can be used to calculate street connectivity specific to assessing performance of DRT. Care should be taken in maintaining the uniformity of distance separation among on-demand nodes distributed along all streets of the network such that no passenger has to walk for more than 1200 feet to reach an on-demand stop. Also, this distance separation should be same for two networks when compared with each other for performance evaluation of DRT. The shuttle operational times are fixed from 6:30 am to 9 pm and the passengers make service requests generated from a typical travel demand hours of the US commuters as shown in Fig. 6 (Data source: Santos et al., 2011). Since the actual cumulative

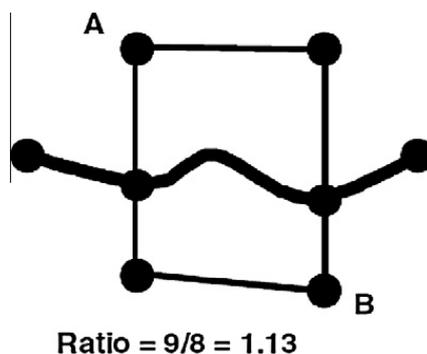


Fig. 4. Link-node ratio connectivity.

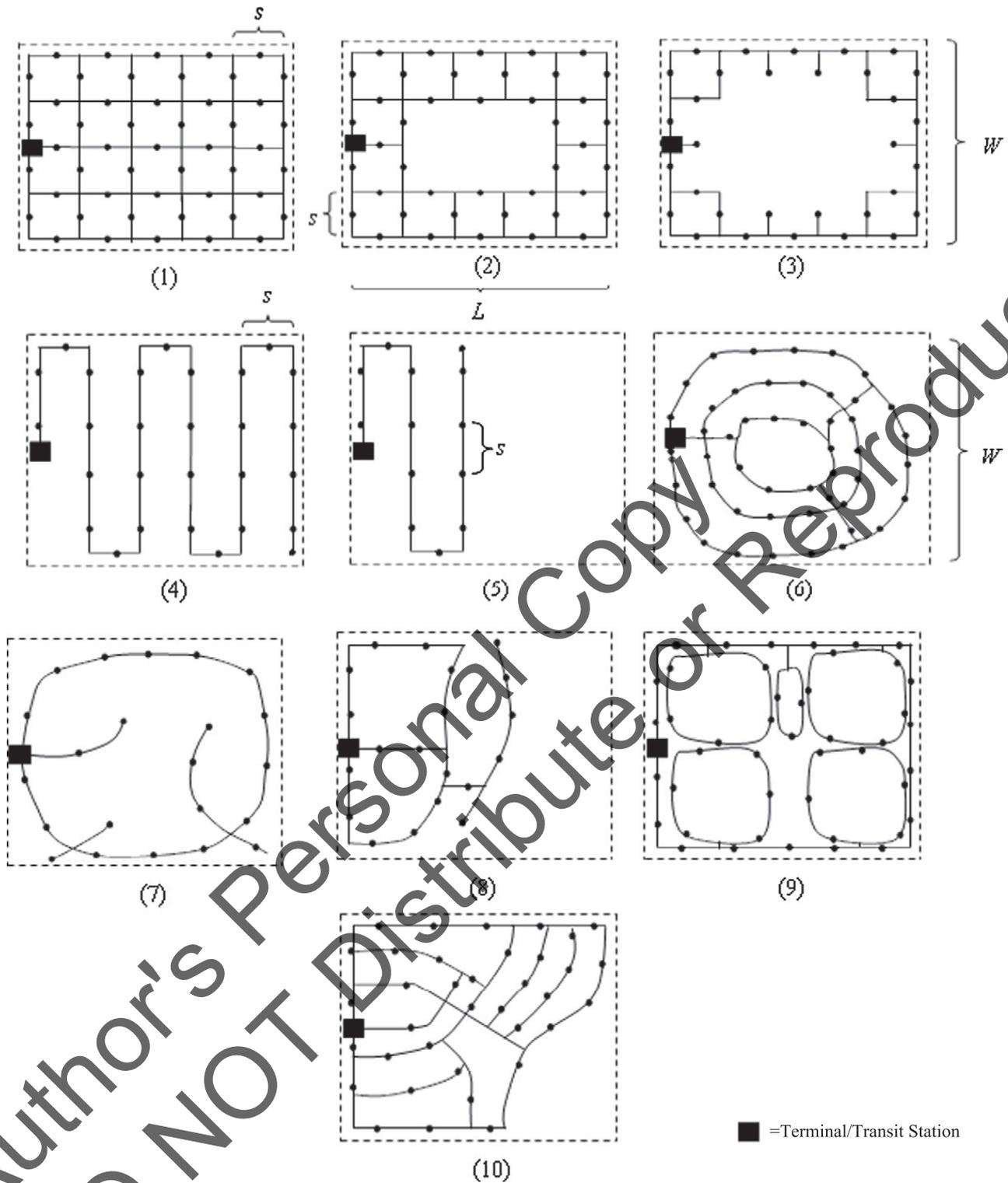


Fig. 5. Examples of existing street patterns.

probability density (derived from real travel time data) was difficult to invert for generating passenger request times, the assumed cumulative density in its linear form was used (see Fig. 6). By using the above assumptions we obtain an average demand of 20–22 passengers per hour. This is typically found in practice from call-n-ride systems operating as demand responsive service (Potts et al., 2010). The value of S_{\min} computed using (9) for these equally sized areas is 0.151 miles. The requests for service are accepted between 6 am through 8:30 pm on phone or internet, are randomly assigned as pick-up (home to terminal) or drop-off (terminal to home) and are spatially uniformly distributed. The sequence at each cycle is computed by using insertion heuristic (Quadrioglio et al., 2007). Insertion does not guarantee optimal routing, but it is

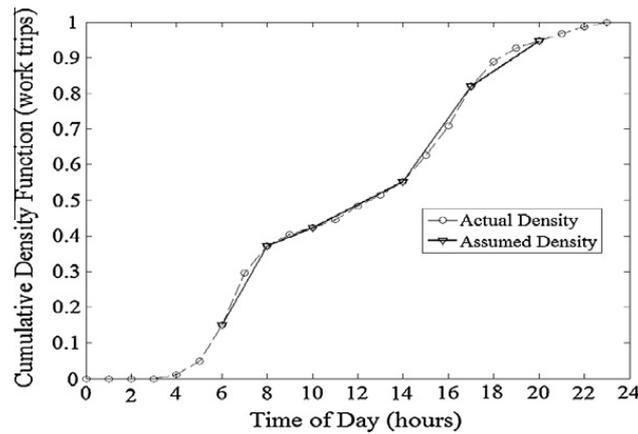


Fig. 6. Cumulative density functions for US work-trips (Santos et al., 2011).

nearly optimal for most scenarios, especially in our applications where the demand nodes to be sequenced are only a few at each cycle. The basic steps underlying the algorithm are as follows (adapted from Li and Quadrioglio, 2010),

Suppose there are n number of passengers $P_1, P_2, P_3, \dots, P_n$, and let $T_1 < T_2 < T_3 < \dots < T_n$ represent their show-up times. The terminal or origin point of the trip is denoted by Q . The insertion algorithm builds customer sequence choosing the minimum additional distance (or time) at each insertion step. The following are the sequence of steps:

1. Insert P_1 : QP_1Q is the only possible route (say, R_1).
2. Insert P_2 : Set of possible routes is QP_2P_1Q , and QP_1P_2Q . Get the route R_2 with the minimum DRT running distance (or time) among the two possible routes. Say, R_2 is route QP_1P_2Q .
3. Insert P_3 : Set of possible routes is $QP_3P_1P_2Q$, $QP_1P_3P_2Q$, and $QP_1P_2P_3Q$. Get the route R_3 with the minimum DRT running distance (or time) among the three possible routes.
4. ...
- n. Insert P_n : Assume the route R_{n-1} is generated by inserting P_{n-1} ; Insert P_n to the route R_{n-1} . Find the route R_n with the minimum DRT running distance (or time) among the n possible routes.

The street based shortest path distance between any two nodes is computed using Dijkstra’s algorithm coded in MATLAB R2008b. Dijkstra’s algorithm is used to find the path of the lowest cost between an origin vertex and a destination vertex through a set of vertices (Dijkstra, 1959). Dijkstra’s algorithm has been widely used for vehicle routing problems (VRPs) in finding shortest paths between nodes in a network, more so in the context of demand responsive services as well (see Uchimura et al. (2002) and Horn (2004)).

In computing the transit performance, we consider service quality as the key factor as the operating costs are almost constant between the considered competing networks, all assumed to use the same vehicle type. As noted earlier, the service quality can be expressed as passengers’ disutility, a weighted sum of expected waiting time and expected in-vehicle travel time, in the ratio of 1/1.8 (Wardman, 2004). The cost of transfer time is not included in the disutility function as there is only a ‘single’ transfer involved at the terminal. This transfer time is eventually equal for all the street networks selected for sim-

Table 1
Connectivity Index/Indicator evaluated for the ten networks.

Network no.	No. of links (e) (†)	No. of nodes (v)	S [Eq. (8)]	Proposed CI [Eq. (11)]	Transportation planning connectivity index		Gamma index		Resulting transit performance	Std. dev.
				Calculated	Calculated	Revised/scaled	Calculated	Revised/scaled		
1	94	75	0.241	0.627	1.253	0.922	0.429	0.803	0.570	0.053
2	80	66	0.246	0.614	1.212	0.892	0.417	0.779	0.580	0.054
3	50	47	0.355	0.425	1.064	0.783	0.370	0.693	0.638	0.085
4	27	28	0.624	0.242	0.964	0.710	0.346	0.647	0.925	0.057
5	12	13	0.222	0.680	0.923	0.679	0.364	0.680	0.546	0.033
6	64	58	0.309	0.488	1.103	0.812	0.381	0.712	0.633	0.049
7	25	25	0.279	0.541	1.000	0.736	0.362	0.678	0.587	0.064
8	25	24	0.249	0.607	1.042	0.767	0.379	0.708	0.575	0.039
9	65	54	0.414	0.365	1.204	0.886	0.417	0.779	0.775	0.050
10	65	50	0.254	0.594	1.300	0.957	0.451	0.844	0.580	0.049

ulation and thus, its inclusion in the disutility function is redundant. The performance values were obtained from an average of ten replications for each of the ten networks shown before in Fig. 5. The simulation output is tabulated in Table 1. The resulting performance reflects the disutility of an average passenger expressed in terms of “hours” followed by its standard deviation.

(†) We would like to remind the readers that the on-demand nodes act as the ‘intersection’ in our study since the demand responsive shuttle can only stop at these designated nodes and nowhere else. Not even the points where two streets appear to crisscross. This is a reasonable assumption for two reasons. First, the demand responsive transit usually operates in a residential community with low-demands and these kinds of services are generally door-to-door with average location of the stops at the mid-point of a street. This literally means that the shuttle does not stop at the intersections for serving passengers. Second, the dwell time for pick-up/drop-off of a passenger at a street is much higher as compared to a standard stopping time of approximately 2 s at the intersection (having only Stop signs) as warranted/required by traffic rules within a residential community. However, for Gamma index and transportation planning C.I. we will count the crisscross point of two or more streets in a network as an intersection and compute the number of links thereof. For example, there is a single link between two on-demand nodes *a* and *b* and no intersection in (I) of Fig. 7. The image in (II) of Fig. 7 has three links among the ‘three’ on-demand nodes *a*, *b*, and *c*, and one intersection – the links emanate from the intersection towards nodes *a*, *b* and *c*. Similarly, the number of links in (III) of Fig. 7 is four, the emanating links from the intersection towards nodes *a*, *b*, *c* and *d*. The number of on-demand nodes and intersections are summed together to represent the ‘total number of nodes’ that go into the calculation of link to node (i.e. total number of nodes) ratios for the networks.

The revised/scaled values in Table 1 are for comparing the variation of the performance versus C.I. for the Gamma index and transportation planning C.I. on the ‘same’ chart as for the proposed C.I. Otherwise, we could have developed two more charts (one each for Gamma index and planning index) just using the ‘Calculated’ values of the C.I. The revised/scaled values in Table 1 were developed using the proposed C.I. value of network (5) as the benchmark, since this gave distinct curves for the performance variation versus C.I. computed using the three methods. For example, the revised/scaled value of transportation planning index of network (10) in Table 1 was calculated using $(0.68/0.923) \times 1.3 = 0.957$. The chart in Fig. 8 illustrates the variation of DRT performances versus different connectivity indicator values. The data entries are exactly the same as in Table 1. The network numbers are displayed beside the data points.

We seek to identify which and whether our C.I. and the other two follow the logical expected relationship “higher connectivity → better performance”. It can be deduced from Fig. 8 that as the transportation planning index and the Gamma index increase along the horizontal *x*-axis, the disutility does not follow with the expected and intuitive decrease (corresponding to a better performance). Gamma index and the planning connectivity index show an unpredictable trend in disutility for the networks used. Thus, the relationship between the performance of other networks and their Gamma index or transportation planning index is extremely erratic. This clearly shows that performance cannot be very well related if the measure of connectivity is used from the graph theory concepts or even that obtained by transportation planning index.

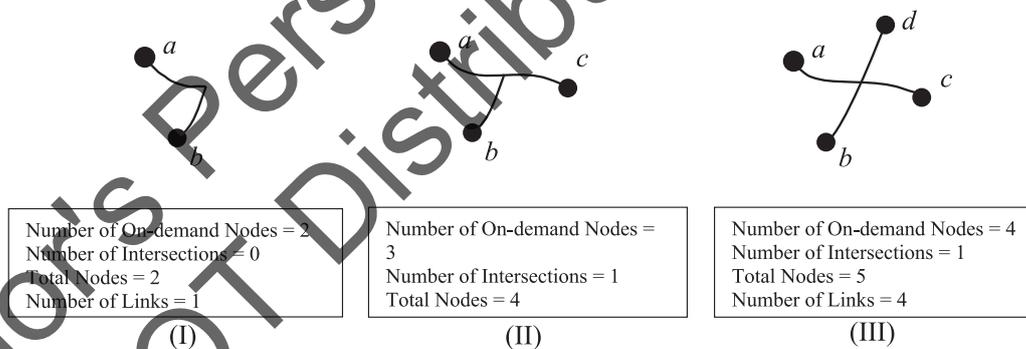


Fig. 7. An example for calculation of number of links and nodes.

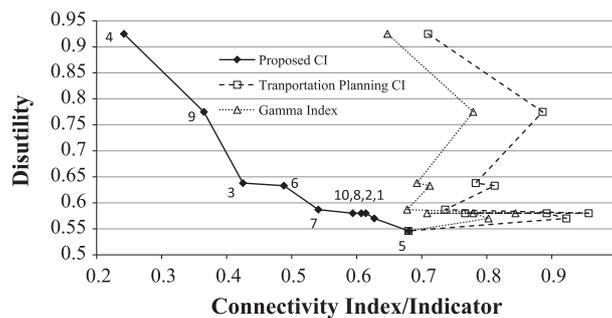


Fig. 8. Variation of DRT performances (disutility) versus different connectivity indicators values.

On the other hand, Fig. 8 shows that there is a direct monotonic relationship between our proposed C.I. and the transit performance between any two diverse residential areas. Therefore, the C.I. is a good predictor. Note that, more realistically, actual demand would not be uniformly distributed across the area (as assumed for simplicity), but likely somewhat evenly distributed along links and stops. This would change the C.I. values and the standing among networks, but would maintain the desired monotonic relationship.

We further show the C.I. effectiveness with another more intuitive example comparing two different networks which have the same exact number and location of nodes and the equal demand at all the nodes. The two networks shown in Fig. 9 (labeled (I) and (II)) have exactly the same layout with the exception that one of the links connected to the depot from a node (Z) in network (II) is missing. The demands at each of the nodes of the two networks are equal. This might reflect a situation in which a decision needs to be made as to whether add a new link to the network. All distances between two neighboring nodes is approximately 350 feet with the whole service area enclosed within a square buffer of length, $L = 700$ feet and width, $W = 700$ feet (though this could be hypothetical but it suffices as an example). All the remaining assumptions such as the travel times, disutility functions and average shuttle speed of 20 mph are same as with the previous simulations carried out across the ten networks before. The C.I. values as well as the DRT performance (disutility) using the two networks are noted for three different daily demands of $\eta = 60, 80$ and 100 . These values are reported beneath the networks of Fig. 9 in the boxes. It is clearly seen from the disutility values that network (I) demonstrates better performance for all demand cases as compared to network (II) and there is clear evidence that a direct relationship exists between the proposed C.I. and DRT performance. Thus, our proposed C.I. also qualifies to be robust enough to compare networks that might have almost identical street layouts and with equal demand distributed over the nodes in reality.

Higher C.I.s correspond to lower disutility values (and higher performance). This information would be quite useful for the transit agencies to assess a transit system's performance for a given network before it is even set-up or put in operation. The C.I. is easily computable for a given demand and approximate geometry of the service area and street layout options can be evaluated with respect to their related transit performance without extensive simulation analyses.

4.1. Effect of demand distribution

In the earlier simulation analyses the demand was assumed to be concentrated over the stops/nodes with every node having a non-zero demand rate value (λ) attached to it. This was simply because of demands that get concentrated on stops/nodes proportional to the land area or catchment area closest to them. The purpose of this section is to capture and validate out proposed C.I. with respect to uneven demand distributions. In this regard, network (6) is further analyzed for performance with four different sets of demand patterns. The street link connections are maintained as the one used earlier over network (6). However, demand is distributed differently at the on-demand nodes depending on their location. The image in Fig. 10 shows four different portions of the network identified as loops – (A–C) and, radially placed nodes on three street segments (counted together as a group) denoted by (D).

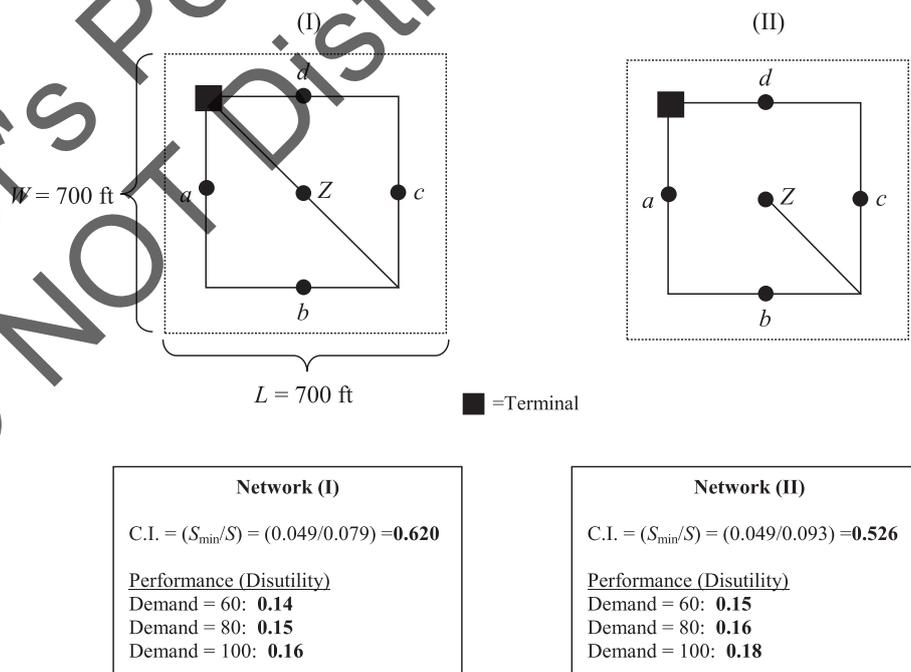


Fig. 9. Network performance for identical nodes with equal demands.

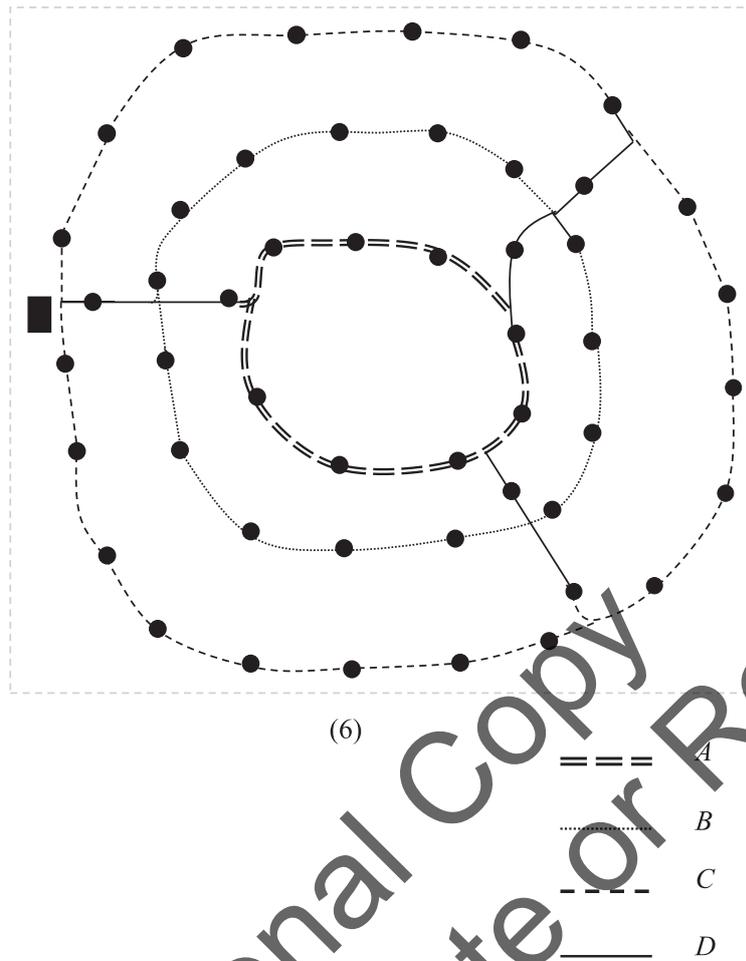


Fig. 10. Different street systems within network (6).

The demand distribution is varied by assuming all demands concentrated at nodes belonging to one of the loops (or segments) and none on the rest. Nodes from a given loop (or segment) have an even demand distribution among themselves. These are identified as four different cases from 1 to 4, where Case (1) corresponds to all the demands concentrated uniformly only over the nodes in loop (A) and none on any of the other loops or segments. Similarly, Case (2) has demands only over nodes in loop (B) and none on other loops (or, segments) and so on. The simulation results for these cases are represented through the charts in Fig. 11 for different total daily demands of $\eta = 200$ passengers.

Different demand distributions within a given network (6) correspond to different values of the connectivity indicator, calculated using Eq. (8) for S. An increase in the proposed C.I. corresponds to a decrease in disutility, as we would have wished to observe. This further validates the versatility and applicability of the proposed C.I. for planning and design purposes over a given street network system.

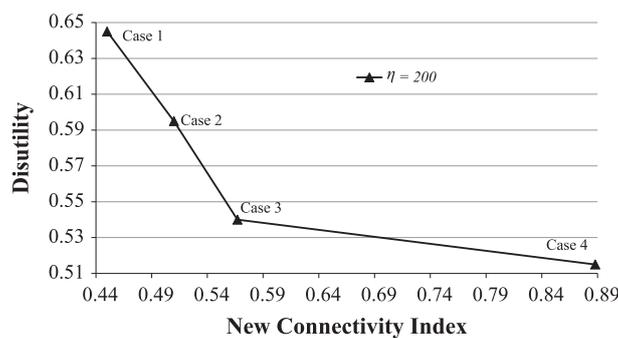


Fig. 11. Disutility versus Connectivity Index variation for different demand distributions.

5. Conclusions

Feeder transit services have been identified as one of the possible solutions of the first/last mile issue for improving transit performance. We have proposed a new Connectivity Indicator (C.I.) able to predict on-demand transit performance, as there is a need of such tools. Currently, there is no indicator as of today in literature that can exclusively gauge DRT performance for a given street network system. The most widely used street connectivity index in transportation is the general accepted one from transportation planning perspective which is inadequate and is potentially faulty for performance prediction of DRT.

The proposed C.I. is defined to be between 0 (worst connectivity) and 1 (ideal “perfect” connectivity) and its values are higher for scenarios showing better demand responsive transit performance. The C.I. is easily computable and this monotonic relationship is very useful as higher C.I. means higher transit performance and serves as a useful tool for planning purposes. Should alternative network street designs be available in a given service area, our index would clarify which design would perform better with respect to a potential DRT service in the area. Comparisons performed by simulation vs. other current indicators demonstrate the validity of the proposed C.I., which is also shown to work properly when varying demand distributions within the same network.

Authors are aware of the limitation of this current research, as several assumptions have been made throughout the C.I. derivation, but also think this novel easily computable indicator may be quite useful after our successful validations. In practice, planners may use the proposed C.I. to evaluate alternatives street network configurations in competition to be implemented in a given residential area and predict how well they would allow an on-demand transit service to perform within the area.

Appendix A

A.1. Example for indicator calculation

Consider a hypothetical continuous street (having a uniform demand distribution across it) is enclosed in a rectangular area of length, $L = 1200$ feet, and width, $W = 800$ feet. Six different on-demand nodes are placed along the street (shown in Fig. A.1). Assume street-based distance (d_{ij} , where, $i = \{1, 2, \dots, 6\}$ and $j = \{1, 2, \dots, 6\}$) between any of two neighboring on-demand nodes = 400 feet. Thus, $d_{12} = d_{23} = d_{34} = d_{45} = d_{56} = d_{61} = 400$ ft. With all the six nodes connected by the street, different combinations of distances along the street can be calculated, for example $d_{14} = d_{12} + d_{23} + d_{34} = 1200$ ft (see Fig. A.1). Also, assume the demand rate at each of the nodes is, $\lambda_1 = 11$ passengers per mile², $\lambda_2 = 12$ passengers per mile², $\lambda_3 = 13$ passengers per mile², $\lambda_4 = 14$ per passengers mile², $\lambda_5 = 15$ passengers per mile² and $\lambda_6 = 16$ passengers per mile². These demand rates are proportional to the approximate shaded area shown around each on-demand node placed along the street (see Fig. A.1). This follows from the uniform spatial demand assumption which is constant over the area enclosed within the rectangle. For non-uniform spatial demand distribution, the demand rates can also be appropriated by the population surrounding the node that could potentially use the given node for service.

The sum of demand rates $\Lambda = \sum_{i=1}^6 \lambda_i = 81$ passengers.

For $L = 0.23$ miles, $W = 0.15$ miles, the value of the numerator of the C.I. in Eq. (11), S_{min} , is,

$L = 1200$ feet (0.23 miles)

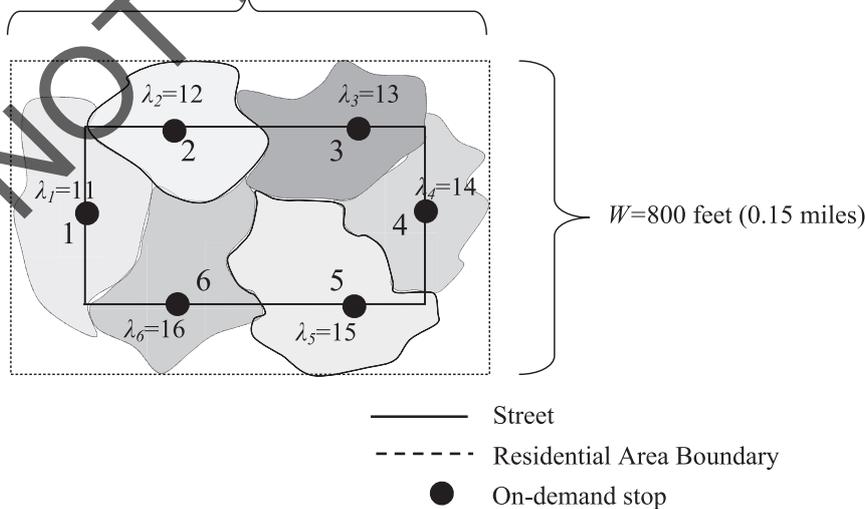


Fig. A-1. An example case for indicator calculation.

$$S_{\min} = \frac{\sqrt{L^2 + W^2}}{3} + \frac{L^2}{6W} \ln \left(\frac{W + \sqrt{L^2 + W^2}}{L} \right) + \frac{W^2}{6L} \ln \left(\frac{L + \sqrt{L^2 + W^2}}{W} \right) + \frac{L^5 + W^5 - \sqrt{(L^2 + W^2)^5}}{15L^2W^2} = 0.068 \text{ miles}$$

For node $i = 1$,

$$\sum_{j=1, j \neq 1}^{j=6} \lambda_j d_{1,j} = (12 \times 400 + 13 \times 800 + 14 \times 1200 + 15 \times 800 + 16 \times 400)/5280 = 10.3 \text{ passenger-miles}$$

Similarly,

For node $i = 2$,

$$\begin{aligned} \sum_{j=1, j \neq 2}^{j=6} \lambda_j d_{2,j} &= (11 \times 400 + 13 \times 400 + 14 \times 800 + 15 \times 1200 + 16 \times 800)/5280 = (51600/5280) \\ &= 9.77 \text{ passenger-miles} \end{aligned}$$

For node $i = 3$,

$$\begin{aligned} \sum_{j=1, j \neq 3}^{j=6} \lambda_j d_{3,j} &= (11 \times 800 + 12 \times 400 + 14 \times 400 + 15 \times 800 + 16 \times 1200)/5280 = (50400/5280) \\ &= 9.55 \text{ passenger-miles} \end{aligned}$$

For node $i = 4$,

$$\begin{aligned} \sum_{j=1, j \neq 4}^{j=6} \lambda_j d_{4,j} &= (11 \times 1200 + 12 \times 800 + 13 \times 400 + 15 \times 400 + 16 \times 800)/5280 = (46800/5280) \\ &= 8.86 \text{ passenger-miles} \end{aligned}$$

For node $i = 5$,

$$\begin{aligned} \sum_{j=1, j \neq 5}^{j=6} \lambda_j d_{5,j} &= (11 \times 800 + 12 \times 1200 + 13 \times 800 + 14 \times 400 + 16 \times 400)/5280 = (45600/5280) \\ &= 8.64 \text{ passenger-miles} \end{aligned}$$

For node $i = 6$,

$$\begin{aligned} \sum_{j=1, j \neq 6}^{j=6} \lambda_j d_{6,j} &= (11 \times 400 + 12 \times 800 + 13 \times 1200 + 14 \times 800 + 15 \times 400)/5280 = (46800/5280) \\ &= 8.86 \text{ passenger-miles} \end{aligned}$$

The denominator of the proposed connectivity indicator, S , is,

$$\begin{aligned} S &= \frac{1}{A} \left(\lambda_1 \frac{\sum_{j=1, j \neq 1}^{j=6} \lambda_j d_{1,j}}{A - \lambda_1} + \lambda_2 \frac{\sum_{j=1, j \neq 2}^{j=6} \lambda_j d_{2,j}}{A - \lambda_2} + \lambda_3 \frac{\sum_{j=1, j \neq 3}^{j=6} \lambda_j d_{3,j}}{A - \lambda_3} + \lambda_4 \frac{\sum_{j=1, j \neq 4}^{j=6} \lambda_j d_{4,j}}{A - \lambda_4} + \lambda_5 \frac{\sum_{j=1, j \neq 5}^{j=6} \lambda_j d_{5,j}}{A - \lambda_5} + \lambda_6 \frac{\sum_{j=1, j \neq 6}^{j=6} \lambda_j d_{6,j}}{A - \lambda_6} \right) \\ &= \frac{1}{81} \left(\frac{11 \times 10.3}{(81 - 11)} + \frac{12 \times 9.77}{(81 - 12)} + \frac{13 \times 9.55}{(81 - 13)} + \frac{14 \times 8.86}{(81 - 14)} + \frac{15 \times 8.64}{(81 - 15)} + \frac{16 \times 8.86}{(81 - 16)} \right) \\ &= \frac{1}{81} \left(\frac{113.3}{70} + \frac{117.2}{69} + \frac{124.1}{68} + \frac{124}{67} + \frac{129.6}{66} + \frac{141.7}{65} \right) \\ &= \frac{1}{81} (1.61 + 1.69 + 1.83 + 1.85 + 1.96 + 2.18) = 0.137 \text{ miles} \end{aligned}$$

Thus, from Eq. (11), connectivity Indicator (C.I.) = $(S_{\min}/S) = (0.068/0.137) = 0.496$

References

- Badami, M.G., Haider, M., 2007. An analysis of public bus transit performance in Indian cities. *Transportation Research Part A* 41 (10), 961–981.
- Cervero, R., Kockelman, K., 1997. Travel demand and the 3Ds: density, diversity, and design. *Transportation Research Part D* 2 (3), 199–219.
- Chandra, S., Shen, C.W., Quadrioglio, L., 2011. A simulation study to derive the optimal cycle length for feeder transit services. *International Journal of Information Systems in the Service Sector* 3 (3), 27–46.
- Derrible, S., Kennedy, C., 2009. Network analysis of world subway systems using updated graph theory. *Transportation Research Record: Journal of the Transportation Research Board* 2112, 17–25.
- Derrible, S., Kennedy, C., 2010a. Characterizing metro networks: state, form, and structure. *Transportation* 37 (2), 275–297.
- Derrible, S., Kennedy, C., 2010b. The complexity and robustness of metro networks. *Physica A* 389 (17), 3678–3691.

- Dijkstra, E.W., 1959. A note on two problems in connexion with graphs. *Numerische Mathematik* 1 (1), 269–271.
- Dill, J., 2004. Measuring network connectivity for bicycling and walking. *Joint Congress of ACSP-AESOP*.
- Fielding, G.J., Babitsky, T.T., Brenner, M.E., 1985. Performance evaluation for bus transit. *Transportation Research Part A* 19 (1), 73–82.
- Fitzpatrick, K., Hall, K., Perkinson, D., Nowlin, L., Koppa, R., 1996. Guidelines for the Location and Design of Bus Stops. *TCRP Report 19*.
- Frank, L.D., Stone, B., Bachman, W., 2000. Linking land use with household vehicle emissions in the central Puget Sound: methodological framework and findings. *Transportation Research Part D* 5 (3), 173–196.
- Fu, L., 2002. A simulation model for evaluating advanced dial-a-ride paratransit systems. *Transportation Research Part A* 36 (4), 291–307.
- Gaboune, B., Laporte, G., Soumis, F., 1993. Expected distances between two uniformly distributed random points in rectangles and rectangular parallelepipeds. *Journal of the Operational Research Society*, 513–519.
- Gleason, J.M., Barnum, D.T., 1982. Toward valid measures of public sector productivity: performance measures in urban transit. *Management Science* 28 (4), 379–386.
- Gupta, D., Chen, H.W., Miller, L.A., Surya, F., 2010. Improving the efficiency of demand-responsive paratransit services. *Transportation Research Part A* 44 (4), 201–217.
- Handy, S., Paterson, R.G., Butler, K., 2003. Planning for Street Connectivity: Getting from here to there. No. PAS Report No. 515.
- Horn, M.E.T., 2004. Procedures for planning multi-leg journeys with fixed-route and demand-responsive passenger transport services. *Transportation Research Part C* 12 (1), 33–55.
- Kansky, K.J., 1963. Structure of Transportation Networks: Relationships between Network Geometry and Regional Characteristics.
- Koffman, D., 2004. Operational experiences with flexible transit services. *Transportation Research Board* 53.
- Kostof, S., Tobias, R., 1991. *The City Shaped*. Thames and Hudson London.
- Lam, T., Schuler, H., 1982. Connectivity index for systemwide transit route and schedule performance. *Transportation Research Record* 854.
- Li, X., Quadrifoglio, L., 2010. Feeder transit services: choosing between fixed and demand responsive policy. *Transportation Research Part C* 18 (5), 770–780.
- Mattice, K., 2012. FTA's livability research initiatives. *Transportation Systems for Livable Communities* 40.
- O'Sullivan, S., Morrall, J., 1996. Walking distances to and from light-rail transit stations. *Transportation Research Record: Journal of the Transportation Research Board* 1538, 19–26.
- Peponis, J., Allen, D., Haynie, D., Scoppa, M., Zhang, Z., 2007. Measuring the configuration of street networks. In: the 6th International Space Syntax Symposium, Istanbul, Turkey.
- Peponis, J., Bafna, S., Zhang, Z., 2008. The connectivity of streets: reach and directional distance. *Environment and Planning B* 35 (5), 881–901.
- Potts, J.F., Marshall, M.A., Crockett, E.C., Washington, J., 2010. A Guide for Planning and Operating Flexible Public Transportation Services. No. Project B-35.
- Quadrifoglio, L., Dessouky, M.M., Palmer, K., 2007. An insertion heuristic for scheduling mobility allowance shuttle transit (MAST) services. *Journal of Scheduling* 10 (1), 25–40.
- Quadrifoglio, L., Li, X., 2009. A methodology to derive the critical demand density for designing and operating feeder transit services. *Transportation Research Part B* 43 (10), 922–935.
- Santos, A., McGuckin, N., Nakamoto, H.Y., Gray, D., Liss, S., 2011. Summary of Travel Trends: 2009 National Household Travel Survey. No. FHWA-PL-II-022.
- Steiner, F.R., Butler, K., 2012. *Planning and Urban Design Standards*. Wiley.
- Uchimura, K., Takahashi, H., Saitoh, T., 2002. Demand responsive services in hierarchical public transportation system. *Vehicular Technology, IEEE Transactions on* 51 (4), 760–766.
- Wardman, M., 2004. Public transport values of time. *Transport policy* 11 (4), 363–377.