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An Exploratory Methodology to Incorporate Transfer Location in Transit Spatial Coverage Quantification

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Abstract

To accurately assess the potential for reaching spatially distributed opportunities is essential in meeting transport needs of the community. Existing literatures quantify the transit spatial coverage based on door-to-door travel time. The probability of choosing transit decreases as the overall transit travel time increases. Exclusively relying on transit travel time could not capture the impact of transfer location, of which the impact will be exacerbated in a strong radial transit network. In such transit network environment, travelling to neighbouring suburbs often requires a transfer at city centre or a major transit hub. The transit travel time for these trips could be relatively short and within the acceptable threshold, nonetheless, if transit choice users are required to conduct a transfer at a less convenient location, they would possibly switch to private vehicles. This study considers a small area in Brisbane (10 zones), and it shows that areas in or near to the city centre would have a relatively higher connectivity level over outer zones if only the travel time is considered. By incorporating the transfer location in the network connectivity mapping, it is no longer the case. Zones connected by major bus corridors have a higher connectivity level. This study serves as an exploratory effort to incorporate the transfer location to quantify the transit spatial coverage, in addition to the travel time, and proposes a more accurate model to better represent the spatial limitation for transit travel from a zone.

1. Introduction

A critical factor in public transit planning is to accurately assess the effectiveness of transit service, focusing on the spatial efficiency of service coverage in meeting transport needs of the community. This includes both expanding the service coverage and increasing the efficiency of transit routes (Mishra et al., 2012; Murray, 2003). The performance of any public transit system could be measured by its ability to meet mobility and economic needs efficiently and equitably, in an environmentally sound manner (Mamun et al., 2013).

Mamun et al. (2013) developed a zone-based transit opportunity index to analyse the transit network connectivity level (bus network only) of New Haven based on both transit accessibility (the level of access to the transit system) and transit connectivity (the system's provision of services between origins and destinations). Transit connectivity is a function of directness and transit travel time. The authors used a binary parameter δ_{ijl} to represent the directness of transit route between OD pairs (1 if there is a direct connection and 0 otherwise). As for transit travel time, the authors developed logistic decay function (f_{ijl}) based on door-to-door travel time, to reflect decreasing connectivity with increasing travel time. With very similar concept, Lee et al. (2015) examined zone-to-zone transit network connectivity based on the directness of transit service using two measures: the degree of competitiveness and degree of circuity. The degree of competitiveness is a measure to show how much additional transit travel time in comparison to private vehicle travel time. The degree of circuity measures the additional transit travel time required because of the transit network configuration, as compared to the directly connected hypothetical transit network. Raveau et al. (2011) developed the concept of "angular cost" in route choice, as a function of the angle formed between the origin-destination (OD) straight route with the origin-transfer (OT) straight route, weighted by the Euclidean distance to transfer point, to measure the directness of chosen route. Raveau et al. (2011) discovered that transit users tend to penalise routes that deviate from a direct path to the final destination.

This study proposes a method to include the transfer location in determining the transit spatial coverage. Existing methods use the transit door-to-door travel time as a sole function of spatial coverage, and the impedance of service transfer is counted as an extra travel time. In a radial transit network orientation, travelling from one outer suburb to its neighbouring suburb often require a transfer at city centre, because of the lack of transit services directly connecting outer suburbs. The inconvenience of such trips cannot be captured using only travel time as the sole factor. The impact of transfer location could be exacerbated for the choice transit users (who have access to alternative travel modes), because using an automobile eliminates this particular inconvenience (or impedance). This study seeks to integrate the impact of transfer location to the traditional door-to-door travel time measure, to improve the current practice of transit spatial coverage mapping and connectivity modelling. The findings will contribute to the analysis of transit network and transit performance, which then helps with the evaluation of service delivery strategies.

2. Quantification of Transit Network Connectivity

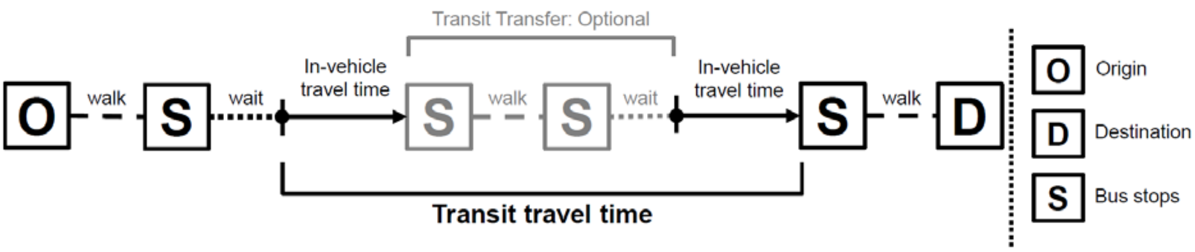
This study seeks to demonstrate how well a transit network is serving a zone (i.e.: SA2) to other zones based on the transit travel time and transfer location as the main impacting factors, using the platform of geographical information systems (GIS). Since the late 1990s, GIS is commonly used to map the accessibility of transit from a specific point (Lei & Church, 2010; Salonen & Toivonen, 2013). In order to quantify zone-to-zone transit network connectivity, it is only possible if each zone is represented by a point of reference, and the assumption that all trips to start and to end at that point (Chang et al., 2002). In transit network studies, zone centroid is generally used as the point of reference, identified using the centre of gravity-based algorithm. This method has been criticised because in reality, these origins and destinations are spatially distributed within zones. For private vehicle travel, zones are small enough that errors resulting from representing origin or destination points using centroid are insubstantial. However, for transit trips, for which the access mode is usually walking, errors from representing an entire zone using a centroid could substantially distort the analysis (Furth et al., 2007). This research uses the largest bus stop (a stop with the most transit routes that pass through) to represent each zone, replacing the existing centroid reference point. This could eliminate the walking components to and from transit stops, and minimise the random effect of intra-zone transfer, based on the assumption that transit riders would assess major stops with more frequent and consistent service.

2.1 Transit Travel Time

Literature has established that travel time should be used to define the level of connectivity, instead of travel distance (Lam & Schuler, 1982; Lee & Lee, 1998; Lei & Church, 2010; Salonen & Toivonen, 2013). Travel distance would not have the ability to capture transit wait times and transfer times, which are perceived to be more onerous than in-vehicle travel times. The concept of transit travel time connectivity decay function is adopted from the connectivity parameter developed by Mamun et al. (2013), motivated by the literature on walking distance decay function for transit demand estimation (Chia et al., 2016; Kimpel et al., 2007; Zhao et al., 2003). These studies stand on the findings that the number of transit user decreases as the walking access to transit facilities increases.

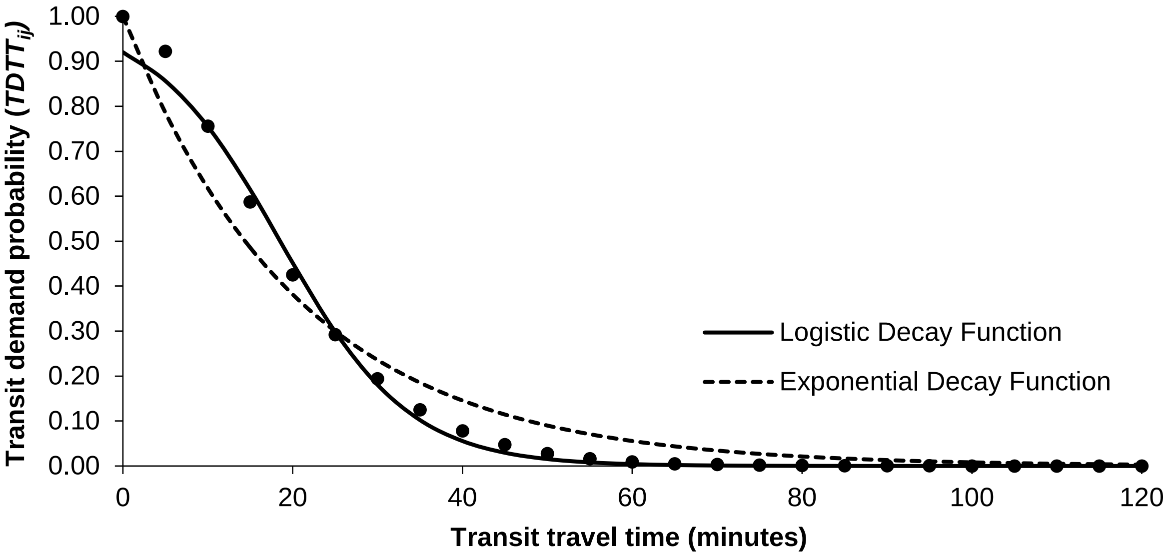
Intuitively, transit users would have a better transit connectivity between an origin-destination pair if it takes less travel time to make a journey. This study relies the five consecutive weekday, from 17 November (Monday) to 21 November 2014 (Friday), morning peak (from the first bus service until 8:30 a.m.) Brisbane “go card” data, regardless of the number of transfers, to study transit travel demand based on transit travel time. It accounts for 137,503 morning peak journeys. Transit travel time of any bus journey is defined as the time when transit rider boards the first bus to the time when transit rider gets off the last bus to destination. Many public bus journeys involve transfer(s) from one route to another, which possibly imply walking from one stop to another and waiting for the next service. Figure 1 illustrates the definition of transit travel time.

Figure 1: Definition of transit travel time



Transit travel times of the 137,503 morning peak journeys were translated into cumulative transit demand probability in 5-minute intervals, as shown in Figure 2. It shows the probability of individual choosing to use transit at different transit travel time. A threshold of 60-minute time gap (from the time when travellers alight a stop, to their next boarding time) is applied to identify whether two transactions are connected as a transfer journey. If transit user stays at a place for more than 60 minutes before making the next trip, those two trips are counted as separate trips, rather than a continuous journey through a transfer. The next process is to distinguish return trips from single-transfer journeys. Studies have shown that transit users are willing to walk on average 400 or 500m to bus stops (Chia et al., 2016; Horner & Murray, 2004; O'Sullivan & Morrall, 1996; Weinstein Agrawal et al., 2008). A maximum distance threshold of 1km from origin and destination is used to distinguish single-transfer journeys from return trips.

Figure 2: Transit travel time decay function



Zhao et al. (2003) adopted a negative exponential function to study the relationship between transit use and walking distance to transit stops. Kimpel et al. (2007) discovered that negative logistic function better estimates the probability of transit use based on walking distance to transit stops. Halás et al. (2014) used a negative logistic function to study the relationship between daily travel flow and distance to regional centres in the Czech Republic. Similarly, Mamun et al. (2013) utilised a logistic function to estimate the transit connectivity level based on door-to-door transit travel time. In this study, both exponential and logistic functions are drawn to estimate the probability of individual choosing bus, based on bus travel time.

From Figure 2, the negative logistic decay function has a better goodness of fit as compared to exponential decay function. Unlike the exponential function, a negative logistic function has the ability to reflect a more gradual rate of reduction of transit use at the initial stage (as bus travel time increases up to 10 minutes), followed by a steeper decline until 30 minutes of bus travel time. The transit demand continues to decrease gradually up to 60 minutes. Once the bus travel time exceeds 60 minutes, the transit demand is near to 0. This is consistent with the findings from other studies (Lee et al., 2015; Mamun et al., 2013) that transit use will begin to deteriorate as transit travel time increases.

The functional form of the logistic decay function is expressed in Equation 1, of which the coefficient values of α and β are estimated using the cumulative transit demand. This transit demand decay function is later applied to reflect the probability of transit use as transit travel time increases. Transit demand probability refers to the probability of an individual choosing to take transit, based on transit demand analysis, to reflect the choices and behaviours of transit users.

$$TDTT_{ij} = \frac{L}{1 + \alpha e^{-\beta t}} \qquad \textbf{Equation 1}$$

where,

$TDTT_{ij}$ = Transit demand probability based on travel time from origin i to destination j
L = The upper limit of the logistic decay curve (assumed to be 1.0 in this study)
α = 0.0755443
β = – 0.1383489
t = Transit travel time (minutes)

2.2 Transit Transfer Location

When a traveller is required to make a transfer in order to complete a trip, generally, the traveller would consider the location of transfer. If the transfer location is substantially deviated from the "preferred transfer locations", it will decrease the utility of public transit, and eventually deter the use of public transit. Table 1 shows the composition of bus journey trips based on the number of transfers and corresponding transit demand probability. Out of 137,503 morning peak bus journeys, 87.91% of them did not involve any service transfer and 11.47% of them involved one transfer. Journeys with no transfer and one transfer amounted to 99.38% of the total five days' trip data. Since the number of bus journeys with more than one service transfer was negligibly small (less than 0.62%), those trips were excluded from the analysis.

Table 1: Composition of journeys based on number of transfers

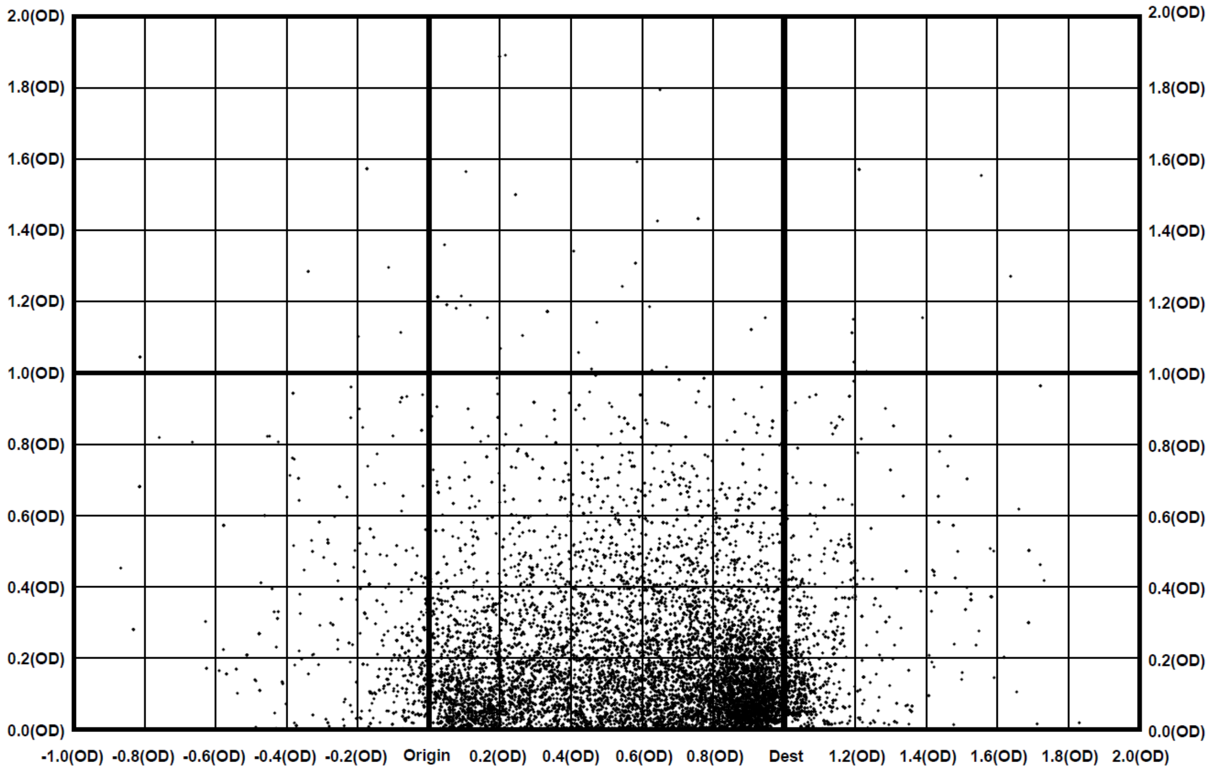
Number of Transfers	Number of Journeys	Percentage	Transit demand probability
0	120,874	87.91%	1.00
1	15,777	11.47%	Varied based on transfer location map
2	800	0.58%	0.00
3	52	0.04%	0.00
4	0	0.00%	0.00
Total	137,503	100.00%	-

As shown in Table 1, solely based on transfer location, if there is a direct service connecting one SA2 to another SA2, the probability to use transit is 1.00; otherwise, if it requires more than one transfer, the probability to use transit is reduced to 0.00. When there is only one transfer required to complete any bus journey, a specific value (between 1.00 to 0.00) will be given based on the transfer locations.

The transfer locations of the 15,777 journeys (one transfer journey) are mapped out on a standardised Euclidean space to infer the preferred transfer locations. The transit journey data may be illustrated as a triangle where each point of triangle represents the coordinate of trip origin, destination. The size of the journey triangles varies by the actual trip distance and therefore the journey data needs to be converted into a homogeneous coordinate system to analyse the spatial distribution pattern, using a series of Euclidean transformations (translation, rotation and compression/dilation).

To analyse the spatial distribution pattern of the transfer points, this study used the grid-based hierarchical clustering method, which combines the grid-based clustering and hierarchical clustering methods. For grid-clustering, each grid is defined as 0.2×OD (origin to destination) unit distance increment. Figure 3 shows the clear concentration of transfer points in the cells, along the straight route distance between the origin and destination, in reference to 1.0×OD unit distance.

Figure 3: Grid structure on transfer location map



This study is based on the hypothesis that Figure 3 represents the "preference" for transfer location of the travellers in the study area. The cell density of each 0.2 OD grid is calculated and shown in Figure 4.

Figure 4: Cell density of transfer locations

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	
10	0.00%	0.00%	0.00%	0.00%	0.00%	0.02%	0.01%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	10
9	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.01%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	9
8	0.00%	0.00%	0.00%	0.00%	0.02%	0.01%	0.01%	0.01%	0.03%	0.00%	0.00%	0.02%	0.01%	0.00%	0.00%	8
7	0.00%	0.00%	0.00%	0.01%	0.01%	0.03%	0.00%	0.03%	0.00%	0.00%	0.00%	0.00%	0.00%	0.01%	0.00%	7
6	0.02%	0.00%	0.00%	0.01%	0.01%	0.04%	0.05%	0.02%	0.02%	0.03%	0.03%	0.04%	0.01%	0.00%	0.00%	6
5	0.00%	0.01%	0.02%	0.03%	0.08%	0.10%	0.11%	0.24%	0.11%	0.17%	0.12%	0.03%	0.01%	0.02%	0.00%	5
4	0.03%	0.00%	0.01%	0.07%	0.05%	0.21%	0.40%	0.56%	0.68%	0.46%	0.11%	0.03%	0.04%	0.01%	0.00%	4
3	0.01%	0.00%	0.03%	0.13%	0.30%	0.45%	0.86%	1.57%	1.67%	1.36%	0.61%	0.06%	0.10%	0.04%	0.00%	3
2	0.03%	0.01%	0.13%	0.14%	0.82%	2.59%	2.74%	3.34%	5.01%	5.66%	1.40%	0.13%	0.18%	0.05%	0.00%	2
1	0.00%	0.01%	0.16%	0.16%	1.53%	9.57%	7.13%	7.79%	10.38%	24.52%	4.41%	0.33%	0.05%	0.01%	0.01%	1

Origin (between E and F) — Destination (between J and K)

The five days morning peak transfer pattern concentrates towards the destination point. The most concentrated cell is J1, which is followed by I1, where a total of 34.09% of transfer points are gathered. These two cells may be regarded as the most preferred transfer location during the morning peak hours. Transit journeys that require a transfer service in those cells will be perceived as viable, as this increases the likelihood of making a transfer as compared to other cells.

Out of the total bus journeys with one service transfer, 59.40% of them had the transfer location, close to the straight path from origin to destination (i.e., F1, G1, H1, I1, and J1) out of the total 150 cells in the map. It implies that most travellers prefer these transfer point, located along the direction of their trip destination. Moving slightly away from the straight path (cell F2 to J2) has an average cell density of 3.87%. It is observed that bus riders would not mind travelling a little farther from the origin and destination path to make a transfer, respectively at 1.53% (cell E1), 4.41% (cell K1) and 1.40% (cell K2) of the total transfer points. The maximum distance bus riders are willing to travel to make a transfer is to cells H3, I3 and J3, and the average value of 1.53% of total bus users transferred in those cells. All the transfer points in those 16 cells account for 90.67% of the total transfers. The average density (in terms of the number of transfer points) of the remaining cells (134 out of 150 cells) is negligible at 0.07%.

In order to determine the value for each transfer journey based on transfer location, each journey triangle OTD (from zone to zone) will undergo a series of Euclidean transformation to determine which cell the transfer location falls into, and to take the cell density value as the representation of the probability of taking the public bus as shown in Equation 2.

$$TDTL_{ij} = \frac{CD}{CD_{max}}$$ **Equation 2**

where,

$TDTL_{ij}$ = Transit demand probability based on transfer location from origin i to destination j (one transfer journey only)

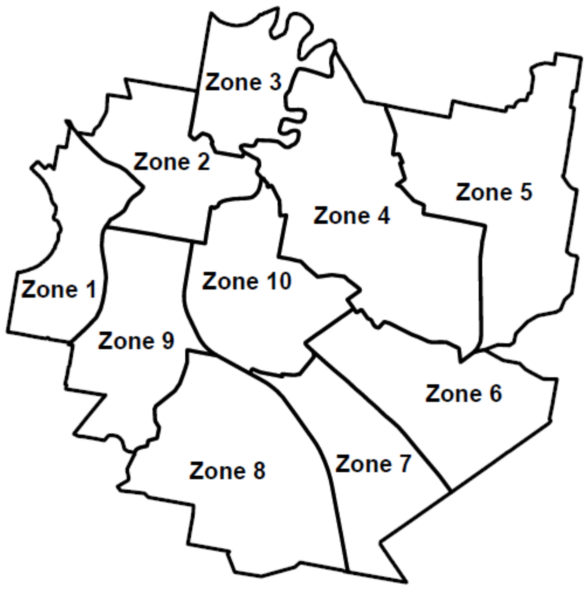
CD = Cell density of the respective cell

CD_{max} = The highest value of cell density among all cells

3. Transit Service Coverage Mapping

For illustration purpose, this study considers a small area in Brisbane (10 zones) as shown in Figure 5.

Figure 5: Sample study area



3.1 Transit Zone Specific

The first step is to determine the point of reference for each zone, represented by the largest bus stops. Next, travel time of each OD pair is retrieved using the GTFS data, departing at 8.00am in the morning. Table 2 shows the bus travel time from one zone to another.

Table 2: Bus travel time from zone to zone of the 10-zone study area

To / From	Zone to zone bus travel time (minutes)									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1		5	17	21	24	35	9	15	3	7
2	10		12	7	10	13	4	12	19	2
3	16	11		13	13	20	15	28	10	13
4	14	5	15		4	7	14	24	26	12
5	15	8	13	4		18	17	28	30	15
6	30	14	30	12	23		22	14	27	20
7	15	5	15	15	24	22		7	20	3
8	29	15	24	39	45	46	3		13	22
9	7	7	14	27	30	40	24	13		22
10	12	2	11	13	21	10	2	19	21	

Using the transit demand probability function developed using transit smart card data, the probability to choose bus from one zone to another zone based on transit travel time is estimated, as shown in Equation 1. For example, it takes 7 minutes to travel from Zone 9 to Zone 1 using bus, and 40 minutes from Zone 9 to Zone 6. The probability to choose public bus as the mode of travel from Zone 9 to Zone 1, and Zone 9 to Zone 6 can be calculated as follows:

$$TDTT_{91} = \frac{1}{1+\ 0.0755443e^{0.1383489\ (7)}} = 0.90$$

$$TDTT_{96} = \frac{1}{1+\ 0.0755443e^{0.1383489\ (40)}} = 0.13$$

From the calculation, when the bus travel time increases from 7 minutes to 40 minutes, the probability of using bus decreases from 90% to 13%. Table 3 shows the probability of using bus for each OD pair based on the zone-to-zone bus travel time. Those probability values are a good representation of the network connectivity for each pair of zones, which shows the likelihood of travelling using bus. Figure 6 shows the transit network connectivity based on bus travel time, originating from Zone 9. Zone 9 is selected as the origin zone for illustration purposes.

Table 3: Transit demand probability based on bus travel time

To / From	Zone to zone transit demand probability based on bus travel time									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1		0.92	0.72	0.61	0.52	0.22	0.87	0.77	0.94	0.90
2	0.86		0.83	0.90	0.86	0.81	0.93	0.83	0.67	0.94
3	0.75	0.84		0.81	0.81	0.64	0.77	0.40	0.86	0.81
4	0.79	0.92	0.77		0.93	0.90	0.79	0.52	0.46	0.83
5	0.77	0.89	0.81	0.93		0.70	0.72	0.40	0.34	0.77
6	0.34	0.79	0.34	0.83	0.55		0.58	0.79	0.43	0.64
7	0.77	0.92	0.77	0.77	0.52	0.58		0.90	0.64	0.94
8	0.37	0.77	0.52	0.15	0.08	0.07	0.94		0.81	0.58
9	0.90	0.90	0.79	0.43	0.34	0.13	0.52	0.81		0.58
10	0.83	0.94	0.84	0.81	0.61	0.86	0.94	0.67	0.61	

Figure 6: Transit network connectivity based on bus travel time

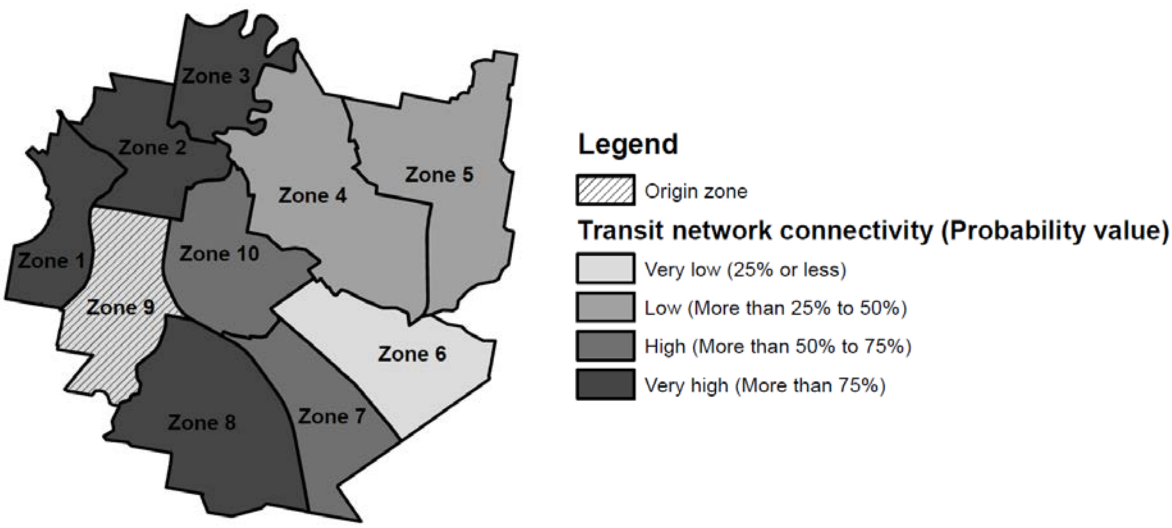


Figure 6 shows an example of the network connectivity based on bus travel time from Zone 9. In general, the transit connectivity of neighbouring zones is higher as the travel times to those zones are relatively short. For example, from Zone 9 to Zone 1, Zone 2, Zone 3 and Zone 8 have a very high connectivity level. Although Zone 10 is located next to Zone 9, the connectivity level is lower (than the first four zones), because a transfer is required. When transfer is involved, it significantly increases the travel time due to additional waiting time, walking time, and in-vehicle travel time. Table 4 shows the total number of transit transfers required to travel from one zone to another.

Table 4: Total number of transit transfers required

To / From	Zone to zone total transit transfers required									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1		0	1	1	1	1	0	0	0	0
2	1		1	0	0	0	0	0	1	0
3	1	1		0	0	0	1	1	0	1
4	1	0	0		0	0	1	1	1	1
5	0	0	0	0		1	1	1	1	1
6	1	0	0	0	1		1	0	1	1
7	1	0	1	1	1	1		0	0	0
8	1	0	1	1	1	1	0		0	1
9	0	0	0	1	1	1	1	0		1
10	1	0	1	1	1	0	0	1	1	

According to Table 4, there is no direct bus service connecting Zone 9 and Zone 10. This supports the literature that formulates the transfer impacts in terms of additional time and cost incurred during transfer (Sharaby & Shiftan, 2012; Wardman et al., 2001). This study challenges the state-of-the-art, and premises on the hypothesis that transit users have a preference for travel direction towards transfer points, which will influence their travel mode choice.

In reference to Table 1 and Equation 2, the probability of choosing bus based on the transfer location will be 1.00, if there is a direct service connecting two zones; the probability will be 0.00, if the travel requires more than one transfer. If one service transfer is required, the corresponding transit demand probability is determined by comparing the transfer location with the transfer map (Figure 3 and Figure 4). For example, travelling from Zone 9 to Zone 5 using bus requires one service transfer. In this journey, the transfer point is located in cell G3 in the transfer map. Similarly, travelling from Zone 9 to Zone 6 requires a transfer at cell F4. The probability to choose public bus to travel from Zone 9 to Zone 5, and Zone 9 to Zone 6, can be calculated as follows:

$$TDTL_{95} = \frac{0.86}{24.52} = 0.03$$

$$TDTL_{96} = \frac{0.21}{24.52} = 0.01$$

Applying the calculation, Table 5 shows the transit demand probability based on transfer location. The transit demand probability drops as the transfer location deviates more from the origin and destination path. For example, the demand probability is 3% when the transfer location is in cell G3. The probability further drops to 1% in cell F4.

Table 5: Transit demand probability based on transfer location

To / From	Zone to zone transit demand probability based on transfer location									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1		1.00	0.03	0.02	0.11	0.03	1.00	1.00	1.00	1.00
2	0.07		0.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00
3	0.02	0.00		1.00	1.00	1.00	0.06	0.03	1.00	0.01
4	1.00	1.00	1.00		1.00	1.00	0.02	0.11	0.01	0.06
5	1.00	1.00	1.00	1.00		0.01	0.02	0.06	0.03	0.23
6	0.29	1.00	1.00	1.00	0.02		0.00	1.00	0.23	0.02
7	1.00	1.00	0.18	0.06	0.02	0.00		1.00	1.00	1.00
8	0.01	1.00	0.06	0.00	0.00	0.00	1.00		1.00	0.00
9	1.00	1.00	1.00	0.02	0.03	0.01	0.00	1.00		0.00
10	0.06	1.00	0.02	0.06	0.11	1.00	1.00	0.00	0.00	

As shown next, the travel time and transfer location factors are integrated for the final presentation of the transit network connectivity. Transit demand probability is formulated as a function of transit travel time and transfer location, as shown in Equation 3.

$$TD_{ij} = TDTT_{ij} * TDTL_{ij}$$ **Equation 3**

where,

TD_{ij} = Transit demand probability from origin i to destination j

$TDTT_{ij}$ = Transit demand probability based on bus travel time from origin i to destination j

$TDTL_{ij}$ = Transit demand probability based on transfer location from origin i to destination j

Table 6 shows the transit demand probability by taking into consideration both transit travel time and transfer location. The greater the probability, the better the bus service is between the origin and destination zones.

Figure 7 shows the final transit network connectivity of the study area, originating from Zone 9.

Table 6: Transit demand probability based on transit travel time and transfer location

To / From	Zone to zone transit demand probability									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1		0.92	0.02	0.01	0.06	0.01	0.87	0.77	0.94	0.90
2	0.06		0.00	0.90	0.86	0.81	0.93	0.83	0.00	0.94
3	0.01	0.00		0.81	0.81	0.64	0.05	0.01	0.86	0.01
4	0.79	0.92	0.77		0.93	0.90	0.01	0.06	0.00	0.05
5	0.77	0.89	0.81	0.93		0.01	0.02	0.03	0.01	0.18
6	0.10	0.79	0.34	0.83	0.01		0.00	0.79	0.10	0.02
7	0.77	0.92	0.14	0.04	0.01	0.00		0.90	0.64	0.94
8	0.00	0.77	0.03	0.00	0.00	0.00	0.94		0.81	0.00
9	0.90	0.90	0.79	0.01	0.01	0.00	0.00	0.81		0.00
10	0.05	0.94	0.02	0.05	0.07	0.86	0.94	0.00	0.00	

Figure 7: Transit network connectivity based on transit travel time and transfer location

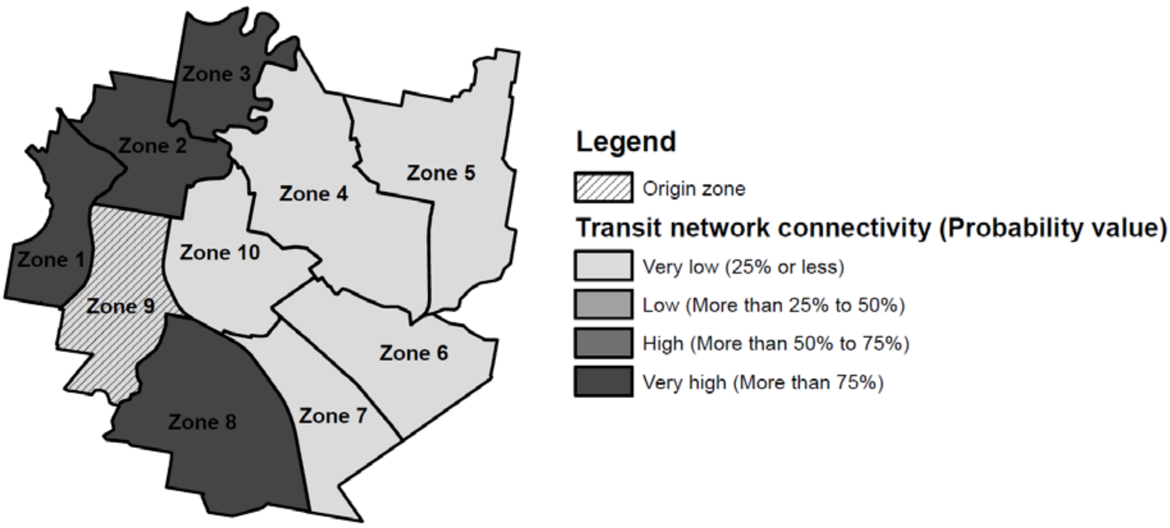


Figure 7 shows that when transfer location is considered, the connectivity level from Zone 9 to Zone 7 and Zone 10 decreases from high to very low. Similarly, it reduces the connectivity level from low to very low for the trips from Zone 9 to Zone 4 and Zone 5. When a transfer is needed to complete a journey, it reduces the probability of travel using bus. It does impose a greater inconvenience to transit users, if transit users are required to conduct a transfer at less convenient transfer locations. This gives a better representation of how well a transit network is connecting each zone.

3.2 Transit Service Coverage of the Study Area

The transit service coverage of a zone is expressed as the average of transit network connectivity (based on transit demand probabilities) from the zone to each of the other zones. If a zone has poor network connectivity to all the other zones, it signifies that this zone has a relatively poor service coverage in the study area. In order to provide a relative transit service coverage level, the average transit demand probability for each zone is normalised by the highest value from all the zones in the study area, as shown in Equation 4.

$$Transit\ Service\ Coverage_i = \frac{\overline{TD}_{ij}}{(\overline{TD}_{ij})_{max}}$$ **Equation 4**

where,

$\overline{TD}_{ij}$ = Average transit demand probability from origin i to destination j

$Transit\ Service\ Coverage_i$ = Transit service coverage level for origin zone i

For example, the transit service coverage for zone 9 is calculated as follows:

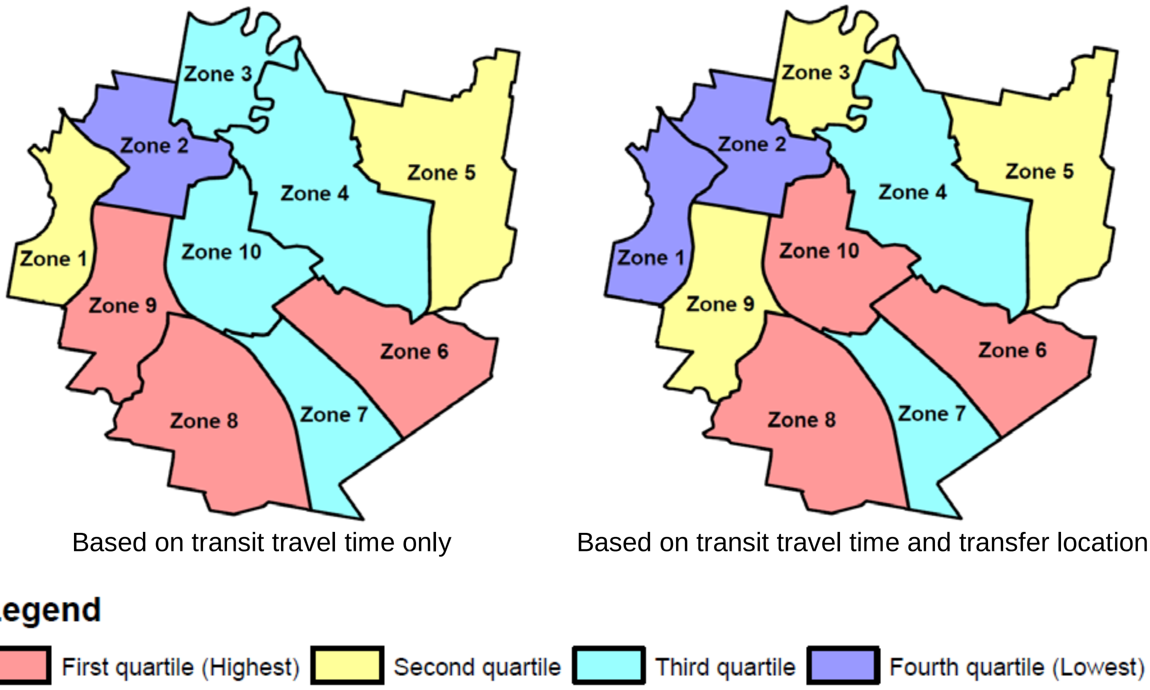
$\text{Transit Service Coverage}_9$

$(\text{Based on transit travel time only}) = \frac{0.60}{0.85}$ = 0.71

$(\text{Based on transit travel time and transfer location}) = \frac{0.38}{0.59}$ = 0.64

Figure 8 shows two transit service coverage maps of the sample study area. The first map shows the transit service coverage based on the transit travel time only. The second map incorporates the transfer location factor.

Figure 8: Transit service coverage of the 10-zone study area



The level of service coverage is illustrated as a relative measure in quartiles. When only the travel time is considered, the service coverage level of Zone 2 and Zone 10 is the highest. These two zones have the greatest spatial coverage. Zone 10 is located at the centre of the study area, where all trips originating from Zone 10 have relatively short travel time. By incorporating transfer location, the service coverage level of Zone 10 drops from the first quartile to the fourth quartile. This implies that most trips originating from Zone 10 to other destination zones require a service transfer at a less convenient location.

If a transit service coverage level is quantified solely based on transit travel time, the service coverage level of Zone 1 belongs to the third quartile. Zone 1 is located on the fringe of the study area, which takes longer time to reach all the other destination zones. By integrating transfer location to the connectivity measure, it improves from the third quartile to the first quartile. Most likely, one of the major transit hubs is located in Zone 1.

4. Conclusion

This study proposes a new approach to quantify the transit service coverage. The conventional measure considers only the transit travel time, and this approach could potentially overestimate the transit service coverage, especially in a strong radial transit network environment. By incorporating the transfer location factor, the transit service coverage could be better captured by reflecting the preference of transit users on travel direction to transfer. It is well established in literature that the increase of transit travel time will reduce the probability of taking public transit as the mode of travel. Likewise, this research demonstrates that individuals have preferences in terms of transfer location. The findings suggest that if transfer(s) is required to complete a journey, an individual would actually consider the travel direction towards a transfer location. If it has deviated from the “preferred transfer location”, it will decrease the utility of public transit. This factor will be more evident in cities with a radial transit network, because passengers are often required to make a transfer only in city centre or major transit hub to catch other transit lines or modes.

As an extension to this research, future study could employ the same method to quantify the transit service coverage of any transit networks, especially those with strong radial network orientation. Future study could quantify the transit demand for each OD pair to identify service gaps so that public investment could be channelled to underserved zones. This study should be viewed as an exploratory work to develop new transit service coverage mapping. The emphasis of this study is only given to the bus network; future works could expand to accommodate the multi-modal transit system.

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Reference list

Chang, K. T., Khatib, Z., & Ou, Y. (2002). Effects of zoning structure and network detail on traffic demand modeling. *Environment and Planning B: Planning and Design, 29*(1), 37-52. doi: 10.1068/b2742

Chia, J., Lee, J., & Kamruzzaman, M. (2016). Walking to public transit – Exploring variations by socio-economic status. *International Journal of Sustainable Transportation, 10*(9), 805-814. doi: 10.1080/15568318.2016.1156792

Furth, P. G., Mekuria, M. C., & SanClemente, J. L. (2007). Parcel-level modeling to analyze transit stop location changes. *Journal of Public Transportation, 10*(2), 73-91. doi: 10.5038/2375-0901.10.2.5

Halás, M., Klapka, P., & Kladivo, P. (2014). Distance-decay functions for daily travel-to-work flows. *Journal of Transport Geography, 35*, 107-119. doi: 10.1016/j.jtrangeo.2014.02.001

Horner, M. W., & Murray, A. T. (2004). Spatial representation and scale impacts in transit service assessment. *Environment and Planning B, 31*, 785-798. doi: 10.1068/b3046

Kimpel, T. J., Dueker, K. J., & El-Geneidy, A. M. (2007). Using GIS to measure the effect of overlapping service areas on passenger boardings at bus stops. *Urban and Regional Information Systems Association Journal, 19*(1), 5-11.

Lam, T. N., & Schuler, H. J. (1982). Connectivity index for systemwide transit route and schedule performance. *Journal of the Transportation Research Board, 854*(1), 17-23.

Lee, K., & Lee, H.-Y. (1998). A new algorithm for graph-theoretic nodal accessibility measurement. *Geographical Analysis, 30*(1), 1-14. doi: 10.1111/j.1538-4632.1998.tb00385.x

Lee, Y.-J., Choi, J. Y., Yu, J. W., & Choi, K. (2015). Geographical applications of performance measures for transit network directness. *Journal of Public Transportation, 18*(2), 89-110. doi: 10.5038/2375-0901.18.2.7

Lei, T. L., & Church, R. L. (2010). Mapping transit-based access: Integrating GIS, routes and schedules. *International Journal of Geographical Information Science, 24*(2), 283-304. doi: 10.1080/13658810902835404

Mamun, S. A., Lownes, N. E., Osleeb, J. P., & Bertolaccini, K. (2013). A method to define public transit opportunity space. *Journal of Transport Geography, 28*, 144-154. doi: 10.1016/j.jtrangeo.2012.12.007

Mishra, S., Welch, T. F., & Jha, M. K. (2012). Performance indicators for public transit connectivity in multi-modal transportation networks. *Transportation Research Part A: Policy and Practice, 46*(7), 1066-1085. doi: 10.1016/j.tra.2012.04.006

Murray, A. T. (2003). A coverage model for improving public transit system accessibility and expanding access. [journal article]. *Annals of Operations Research, 123*(1), 143-156. doi: 10.1023/a:1026123329433

O'Sullivan, S., & Morrall, J. (1996). Walking distances to and from light-rail transit stations. *Journal of the Transportation Research Board, 1538*(1), 19-26. doi: 10.3141/1538-03

Raveau, S., Muñoz, J. C., & de Grange, L. (2011). A topological route choice model for metro. *Transportation Research Part A: Policy and Practice, 45*(2), 138-147. doi: 10.1016/j.tra.2010.12.004

Salonen, M., & Toivonen, T. (2013). Modelling travel time in urban networks: Comparable measures for private car and public transport. *Journal of Transport Geography, 31*, 143-153. doi: 10.1016/j.jtrangeo.2013.06.011

Sharaby, N., & Shiftan, Y. (2012). The impact of fare integration on travel behavior and transit ridership. *Transport Policy, 21*, 63-70. doi: 10.1016/j.tranpol.2012.01.015

Wardman, M., Hine, J., & Stradling, S. (2001). *Interchange and travel choice*.

Weinstein Agrawal, A., Schlossberg, M., & Irvin, K. (2008). How far, by which route and why? A spatial analysis of pedestrian preference. *Journal of Urban Design, 13*(1), 81-98. doi: 10.1080/13574800701804074

Zhao, F., Chow, L. F., Li, M. T., Ubaka, I., & Gan, A. (2003). Forecasting transit walk accessibility: Regression model alternative to buffer method. *Journal of the Transportation Research Board, 1835*(1), 34-41. doi: 10.3141/1835-05