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Does selection of link influence the O-D matrix estimation from link counts? An experience in Bhubaneswar City

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Abstract

Traffic link counts are predominantly used to estimate/update the Origin-Destination (O-D) matrix. The selection of these link locations is based on defined rules that require knowledge of a prior O-D matrix or flow pattern of the network. However, where both prior O-D matrix and link flow information are not available, the traffic count locations are selected heuristically by the experts. The present study aims to understand variation, if any, in the selection of links for traffic counts and the impact of link selection on estimated O-D matrix when the decision is made by different experts for the same study area. Links counts from locations selected by five experts were used to estimate O-D matrix. It was observed that primary links such as entry/exit links, major arterial roads, and links connecting major intersections were common amongst the selection sets chosen by the experts while the sub-arterial links varied across the selection sets. The O-D matrices estimated based on different input link counts were compared pairwise using Wilcoxon signed-rank test. Statistically significant differences were observed between some of the estimated O-D matrices indicating the influence of selection set on O-D matrix estimation. Therefore, the study highlights the importance of considering multiple set of links for O-D matrix estimation. In the present work a mid-sized urban network of Bhubaneswar city, India is taken as a case study. The O-D matrix was estimated simultaneously for car and motorized two-wheelers.

Keywords: Traffic counting locations; Origin-Destination estimation; Wilcoxon signed-rank test; Expert selection

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1. Introduction

Rapid urbanization and subsequent growth of private vehicle ownership in limited urban spaces have caused an imbalance between demand and supply of transportation infrastructure in emerging nations such as India (Sadhukhan et al., 2016). This imbalance has aggravated traffic congestion, delay, and vehicular emissions, and consequently started affecting the quality of urban life (Cheranchery et al. 2018). Aptly, urban transportation problems have been the focus in several emerging nations (Pucher et al., 2007). Efficient transportation planning and traffic management are the key to overcome urban transportation problems. For formulating solutions to urban transportation problems, travel demand pattern in the form of Origin-Destination (O-D) matrix is a basic input (Yang and Zhou, 1998). Although the O-D matrix is an essential input for transport planning and management studies, several cities in emerging nations do not have O-D matrix (Almasari and Al-Jazzar, 2013). The traditional way of developing O-D matrix from household surveys requires significant financial resources and time (Ehlert et al., 2006) and therefore, is not preferred by most of the city planning authorities in emerging nations. On the other hand, development of O-D matrix from traffic count and sample O-D data is becoming popular as it requires relatively less financial resources and time (Bera and Rao, 2011; Viti, 2008).

The research related to the development of O-D matrix from traffic counts and sample O-D data has been carried out in many facets. Several techniques have been developed for estimating O-D matrix using link counts and sample O-D data (Robillard, 1975; Tamin and Willumsen, 1989; Bell, 1991; Nielson, 1998). These techniques have been used in several software packages such as TransCAD, CUBE, VISUM, etc. which are commercially available and can be used readily by transport planners for estimating O-D matrix. Additionally, several works have been conducted on the selection of an optimal number of links for traffic counts (Yang and Zhou, 1998; Chung, 2001; Ehlert et al., 2006). The link selection rules proposed by these studies require a prior O-D matrix or flow pattern of the network (Viti, 2008). However, the majority of cities in emerging nations do not have a prior O-D matrix (Almasri and Al-Jazzar, 2013). Therefore, for studies which involve real networks with no pre-existing traffic counters or O-D matrix, experts or researchers often use some intuitive and rule-of-thumb criteria for the selection of traffic count links (Almasri and Al-Jazzar, 2013; Savrasovs and Pticina, 2017). In all these studies, only one set of links is selected by the expert and the traffic counts at those locations are used for estimation of O-D matrix. In such contexts, it is important to understand if there is any variation in the selection of links by different experts for the same network and its impact on O-D matrix estimation. With this background, this paper aims to investigate two issues (i) Variation, if any, in the selection of links for the traffic counts by different experts; and (ii) impact of variation in link selection on O-D matrix estimation. The work is demonstrated with reference to Bhubaneswar, a mid-sized city in India.

The remainder of the manuscript is organized as follows. A brief description of study area is given in Section 2, while the methodology used in the present work is explained in section 3. The database development is discussed in section 4. Section 5 includes a detailed discussion on results. Finally, the study outcomes are summarized in Section 6.

2. Study Area

In the present work Bhubaneswar City, the capital of Odisha state, India is taken as the case study. The population of the city is about 0.88 million (Chandramouli, 2011). The municipal area of Bhubaneswar city (under Bhubaneswar Municipal Corporation, BMC) is spread over 135 sq. km and the area covered under Bhubaneswar Development Authority (BDA) is about 233 sq. km. As of 2011, the length of road network within BMC was reported to be 1265 km, which included a 36 km National Highway stretch passing through the city. The study area boundary has been delineated by Nandankanan area in the north and BMC boundaries in the south, east, and west.

The city traffic comprises of various modes such as motorized two-wheelers (MTW), private cars, auto-rickshaws (three-wheeler passenger vehicle), buses, commercial vehicles, and non-motorized modes. The car ownership is relatively low in the city. In 2013, only 16 % of the registered vehicles were cars while 74% of the registered vehicles were motorized two-wheelers (MTW) (Bhide, 2015). The city public transport (bus) services started its operations in 2010 and served 33,000 passengers per day in 2013. Motorized three-wheelers (locally known as auto-rickshaws) are extensively used as a common-carrier mode in the city with an average ridership of

160,000 passengers per day (Housing and Urban Development Department, 2014). These three-wheelers ply in fixed routes along the major corridors in the city. While estimating the O-D matrix of the city, it is important to estimate it mode-wise for cars and MTW simultaneously and also to preload the flows of buses and three-wheelers on the network to emulate the real traffic scenario.

3. Methodology

The methodology followed in the present study is presented in four components namely, (i) selection of links, (ii) estimation of O-D matrices, (iii) validation of estimated matrices, and (iv) comparison of estimated O-D matrices. This section includes a detailed discussion on these components. The methodology framework of the present work is shown in Fig. 1 and discussed below.

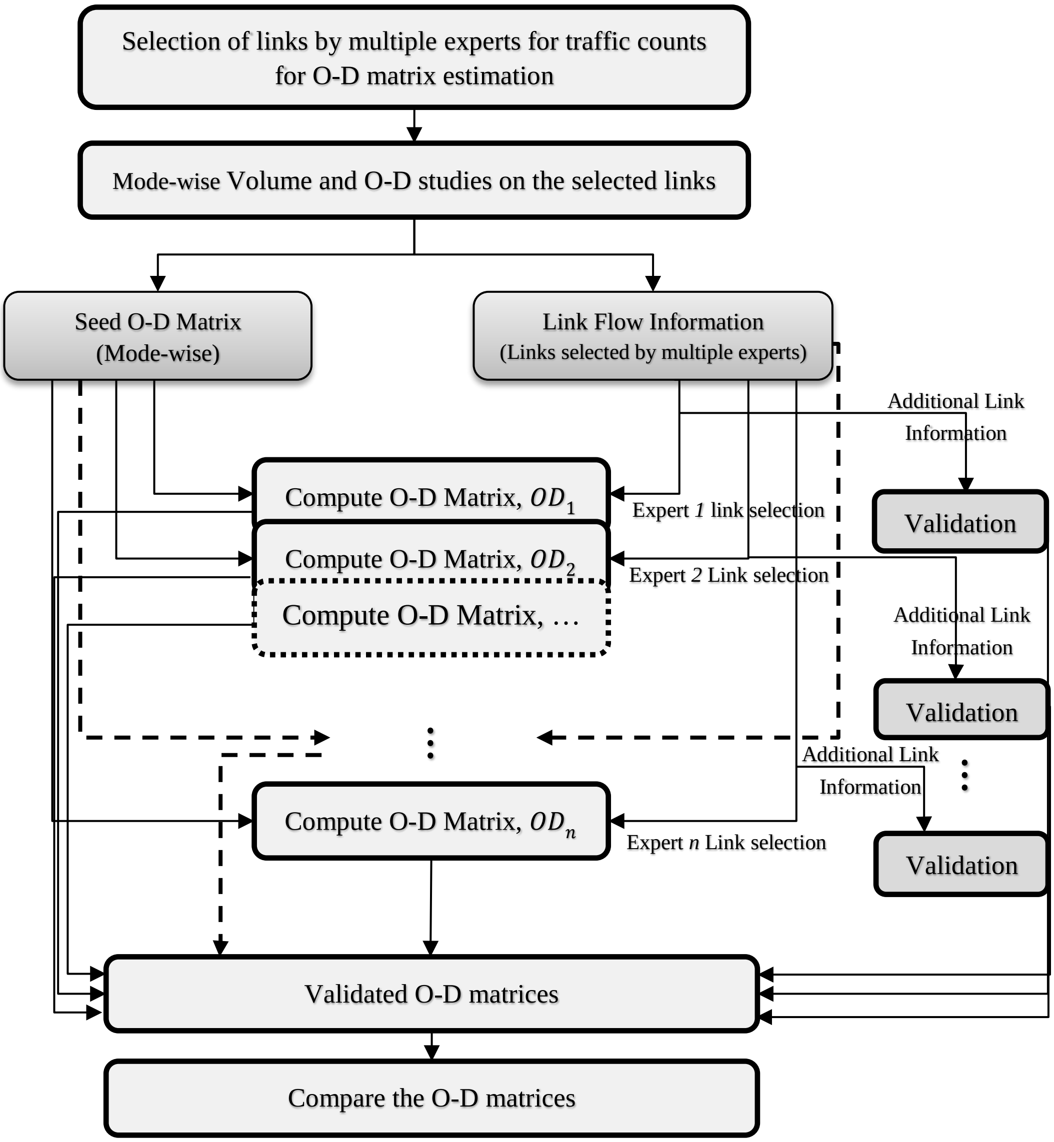

Fig. 1 Methodology Framework

3.1. Selection of Links

Initially, Yang and Zhou (1998) proposed four basic rules namely (i) O-D Covering rule, (ii) maximal flow fraction rule, (iii) maximal flow-intercepting rule, and (iv) link independence rule, for selecting optimal number of traffic counting stations based on the Maximum Possible Relative Error (MPRE) with respect to true O-D matrix. This true O-D is unknown in most cases, and an upper bound matrix based on the prior O-D matrix is often used as a reference O-D matrix. Chung (2001) considered budget constraints by incorporating an upper limit for number of links selected. In continuation with the previous studies, Ehlert et al. (2006) assumed pre-existing detectors in the network and developed a tool with additional weighted importance of link locations for specific O-D flows. This is an efficient tool to find additional locations for new detectors when the prior O-D matrix is available, and detectors pre-exist on certain links in the network. In emerging nations such as India, more often urban areas do not have any prior O-D matrix and traffic counters. Therefore, in cases where prior O-D is not available, researchers/ planners use some intuitive and rule-of-thumb criteria for the selection of traffic count links to estimate the O-D matrix (Viti, 2008).

The present work aims to investigate the variations, if any, in the selection of links for traffic counts by multiple experts, to estimate O-D matrix for the same study area. Five experts (transport planners familiar with the study network) were requested to select a set of locations for traffic counts in the study area. The number of links to be selected by the experts was predetermined to ensure that O-D matrix estimation was not influenced by the number of links. The trip information loss is a function of number of links selected (Khan and Anderson, 2016). Assuming a 5% loss of trip information as acceptable limit, 30% of links in the network (45 links) were selected by the experts. Each expert was also provided with all necessary information such as traffic analysis zones, road network characteristic (road class, number of lanes, divided/undivided carriageway, etc.), land-use pattern, and demographic information. The links selected (45 links each) by different experts may or may not be same. Therefore, all the links selected by experts were combined and the traffic counts were conducted on all the links selected.

3.2. Estimation of mode-wise O-D matrix

Over the years, researchers have used various techniques for estimating O-D matrix based on traffic counts. Although a detailed review of these models is available in the literature (Bera and Rao, 2011; Viti, 2008), a summary of research works of these approaches is given in Table 1.

Table 1. Overview of previous applications of OD estimation techniques

Approach	Authors
Gravity (GR) model	Robillard (1975), Duffus et al. (1987)
Gravity-Opportunity (GO)	Tamin and Willumsen (1989), Gonçalves and Ulyssea-Neto, (1993),Tamin et al. (2003)
Information Minimization (IM) and Entropy Maximization (EM) Approach	Willumsen (1978), Van Zuylen and Willumsen (1980), Bell (1983)
Statistical Approaches (Maximum Likelihood (ML), Generalized Least Squares (GLS) and Bayesian Inference (BI))	Bell (1991), Maher (1983), Bierlaire and Toint (1995), Spiess (1987), Cascetta (1984), Cascetta and Nguyen (1988),
Bi-Level Programming	Spiess, 1990, Yang et al., 1992
Neilsen’s Two Approaches	Nielson (1998), Almasri and Al-Jazzar (2013), Khan and Anderson (2016)
Neural Networks	Gong (1998)
Fuzzy Based Approach	Xu and Chan (1993a, b), Reddy and Chakroborty (1998)
Multi-Vehicle ODM Estimation	Baek et al. (2004), Wong et al. (2005)

Among various approaches mentioned in Table-1, Nielson’s approach was successfully employed on real urban road network (Khan and Anderson, 2016; Almasri and Al-Jazzar, 2013). Moreover, this method can produce reasonable estimates even with an old O-D matrix or a sample O-D matrix as input as the estimate reply more on the available link counts and allow a substantial variation in the seed O-D matrix. Additionally, this technique also addresses the inconsistency in the traffic counts (Khan and Anderson, 2016). Therefore, in this paper, the Multiple Path Matrix Estimation (MPME) method, as proposed by Nielsen (1988) is used for O-D matrix estimation. The input information required are seed O-D matrix (sample O-D matrix from surveys), and traffic link counts. Although the details of this technique are available in Nielson (1998), a brief overview of the technique in the context of the present work is given below.

Nielsen's model uses an iterative (or bi-level) process that changes to and fro between a traffic assignment stage and a matrix estimation stage. The traffic flow between any O-D pair is the summation of expected flow in each route connecting the O-D pair multiplied by the probability to choose that route. The expected traffic along each route is defined as the mean of expected traffic on each traffic link count location along the route. Nielson's Multiple Path Matrix Estimation (MPME) utilizes traffic counts information along all the routes between each O-D pair. Therefore, any inconsistencies in traffic counts in some routes are corrected by adjusting the total expected traffic on the routes between the O-D pair and the average expected traffic on each route. The O-D matrix is then estimated iteratively till the average expected traffic along each route and the sums of the expected traffic on the routes between the concerned zone-pair have converged. Therefore, error due to any inconsistency in the traffic counts is minimized in the case of MPME.

3.3. Validation of estimated matrices

It is necessary to validate the estimated O-D matrices before using them further. Yang et al. (1991) used maximum possible relative error (MPRE) between the estimated O-D matrix and the true (or target) O-D matrix as a measure to validate the estimated matrix with respect to a true matrix. Later Gan et al. (2005) modified MPRE and used Expected Relative Error (ERE) as a measure of validation. However, both these measures require the knowledge of a prior O-D matrix. Bierlaire (2002) used an alternative measure called Travel Demand Scale (TDS) to validate the estimated matrix. Although TDS is independent of prior O-D matrix, the value of TDS depends heavily on the route choice assumptions. Other statistical measures such as (i) Root Mean Square Error (RMSE) to quantify the total error in percent, (ii) Mean absolute error (MAE) to check for over or under prediction, and (iii) Total Demand Deviation (TDD) to understand the quality of estimated O-D matrix are commonly used when true/target values are known (Bera and Rao, 2011). Although no specific thresholds for these measures were suggested, the smaller values of errors indicate a higher quality of the estimated O-D matrix (Bera and Rao, 2011). However, in situations when the true values are not known, these statistical measures cannot be used. In the absence of true or target O-D, Savrasovs and Pticina (2017) used expert opinion to validate the estimated O-D matrix. Researches also used the difference in estimated flow values and input flow values of link flow to validate the estimated O-D matrix (Saraswathy and Isaac 2013, Almasri and Al-Jazzar (2013). In the present study, the estimated O-D matrices were validated based on the assignment of traffic link flows on the links for which count data is available but was not used as input. The estimated matrices are considered to be acceptable when the average error is less than 10% (Almasri and Al-Jazzar, 2013). In this study, User Equilibrium assignment technique was used to incorporate the effect of congestion in the network (Xie et al. 2011). N-conjugate Frank-Wolfe algorithm was employed for this purpose, which is an improvised algorithm of user equilibrium which reduces the computation time by increasing the rate of convergence towards the solution, even though requiring more memory for computation. However, it was shown that considering the value of N to be 2, it results in a bi-conjugate Frank-Wolfe Assignment, which has far less memory requirement than the conventional Frank-Wolfe Assignment techniques (Daneva and Lindberg, 2004).

3.4. Comparison of O-D matrices

The comparison of matrices was made to identify variation in the matrices obtained from different input link given by experts. The comparison was carried out in two stages (i) based on the total trips and trips between each O-D pair of different matrices, and (ii) based on the errors obtained during validation of these matrices.

3.4.1. Based on the total trips and trips between each O-D pair of different matrices

The total trips of two estimated matrices were compared using Total Demand Deviation (TDD) (equation 1). To calculate the maximum error, the denominator is taken as the minimum of total trips amongst the matrices.

$$TDD\% = \frac{|T_1 - T_2|}{T} \times 100 \tag{1}$$

Where
T1 - sum of total trips of O-D Matrix 1
T2 - sum of total trips of O-D Matrix 2
T - minimum of T1, T2

The trips between each O-D pair of two estimated O-D matrices are compared using Wilcoxon Sign-rank Test. This is a non-parametric statistical test used in several studies to compare two related samples from the same population (Woolson, 2007; Corder and Foreman, 2014; Khan and Anderson, 2016).

3.4.2. Based on the errors obtained during validation of these matrices

The O-D matrices estimated based on different input links selected by the experts are assigned on the network. The difference between the assigned flows and the observed links on the input links and the validation links is used to compare the performance of the estimated matrices when assigned onto the network.

4. Database Development

The database development for the present work is summarized under (i) traffic analysis zones (ii) network development (iii) classified traffic counts and sample O-D matrix.

4.1. Traffic Analysis Zones

The Traffic Analysis Zones (TAZs) have been formed based on (a) administrative boundaries (Census zones) (b) land-use pattern (c) road network and screen lines. The city was divided into 43 Traffic Analysis Zones (TAZs), out of which 38 TAZs are internal and five are external. TAZ no. 1 to 38 are internal zones and TAZ no. 39-43 are external zones. Fig. 3 shows the TAZs of the study area.

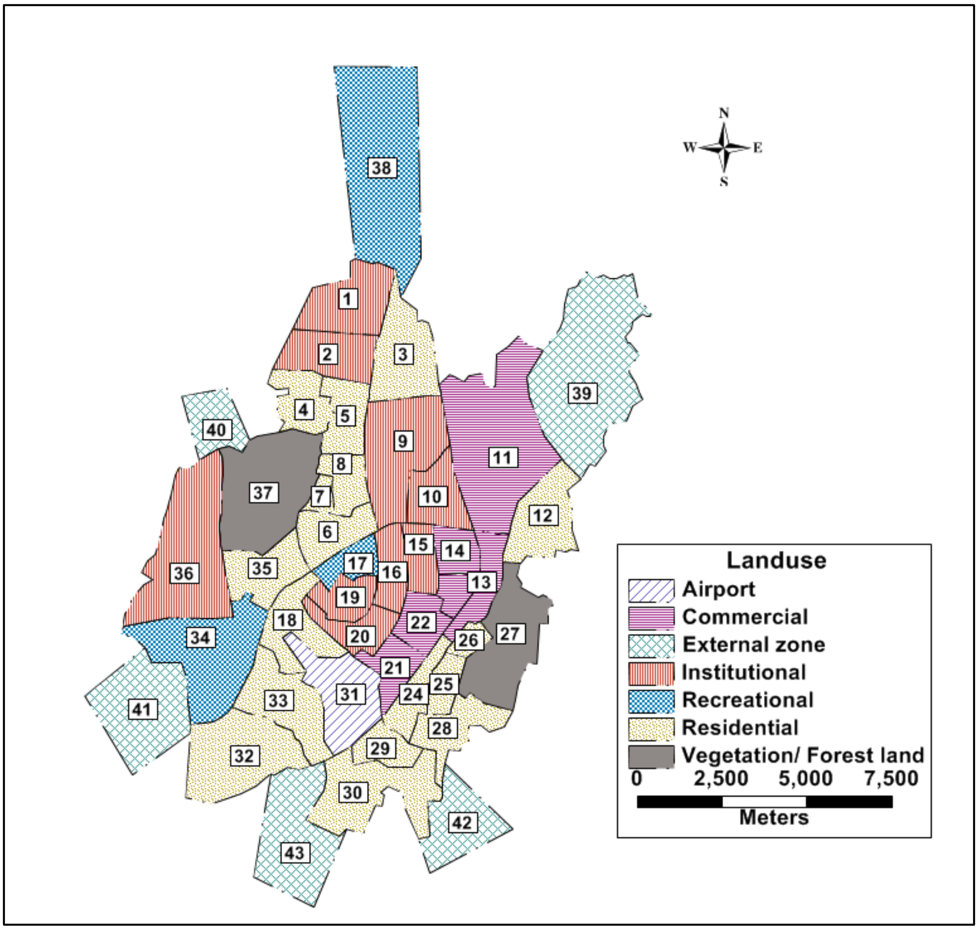

Fig. 2. Traffic Analysis Zones

4.2. Network Development

The road network of Bhubaneswar city was developed on a GIS platform. The road network included National Highway, State Highway, Arterial roads, Sub-Arterial, and collector roads in the study areas. Local roads/streets were ignored from the network and compensated by zone connectors. These zone connectors are only utilized at the beginning and end of a trip. The link information was obtained from a citywide survey. The attribute values of the link such as link ID, capacity, free flow speed, and other relevant information were assigned to the network. The major part of the city traffic comprises of a heterogeneous mix of private vehicles and a relatively lower share of public transport. The road links and intersection composition in the network are summarized in Table 2.

Table 2. Network Information

Road type (functionality)	No of Links	Intersection Type	Number
Arterial	48	Controlled 4-leg	14
Sub-Arterial	105	Uncontrolled 4-leg	3
		Controlled 3-leg	13
		Uncontrolled 3-leg	24

Until 2010, the city's public transportation need was primarily catered by shared three-wheeler passenger vehicles (locally known as shared auto-rickshaw service), after which Govt. of India introduced city buses under Jawaharlal Nehru National Urban Renewal Mission (JnNURM) scheme (Bhide, 2015). Currently, 130 buses are deployed over 18 different routes to serve the city during 7:00 am and 9:00 pm with a headway ranging from 15 mins to 40 mins. Shared three-wheeler service is a para-transportation mode having a carrying capacity of about 4-7 passengers (depending on the size of the vehicle) and ply on fixed routes. There are ten major routes in the city where the shared three-wheelers operate with an average headway as low as 15 seconds during the peak hours.

Both buses and shared three-wheelers operate on fixed routes. The volume of shared three-wheelers is governed by the headway of the service and the volume of buses on links depends on the schedule of the bus service. The volume of buses and shared three-wheelers are preloaded onto the network to replicate more realistic scenarios. The city bus and shared-auto service routes are shown in Fig. 2.

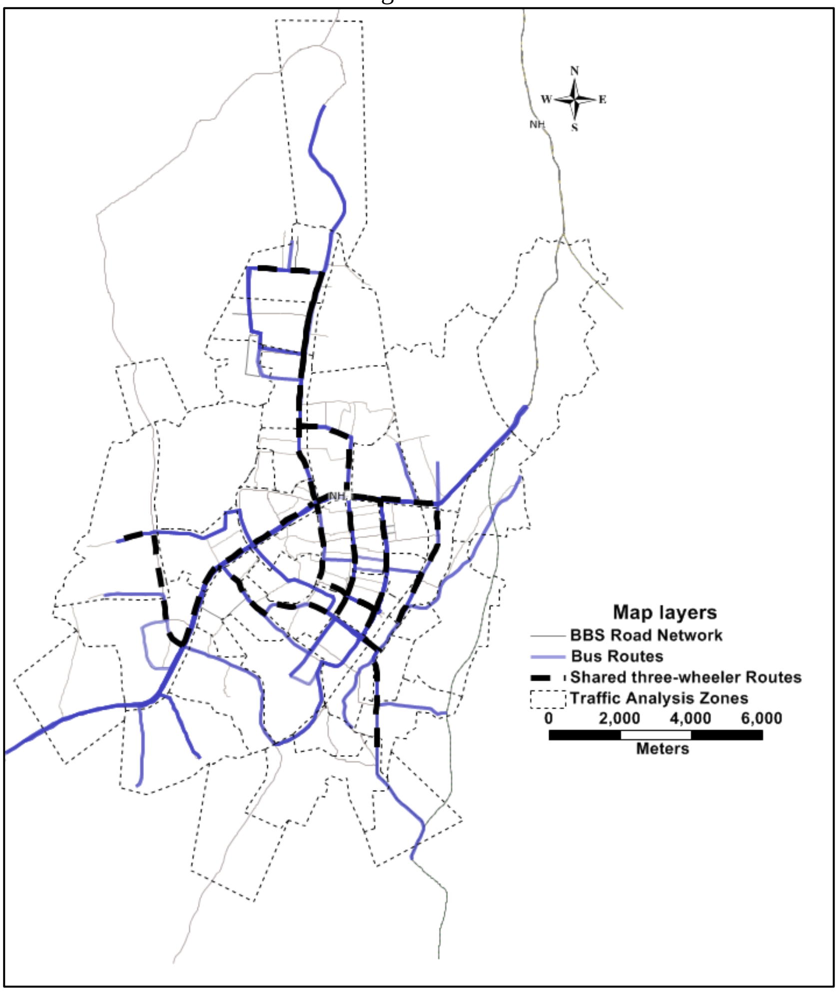

Fig. 3. City bus and shared-auto operating routes

4.3. Classified Traffic Volume and Sample OD Matrix

Based on the selection sets provided by the experts a total of 57 unique locations were selected for traffic link counts, and are presented in Fig. 4.

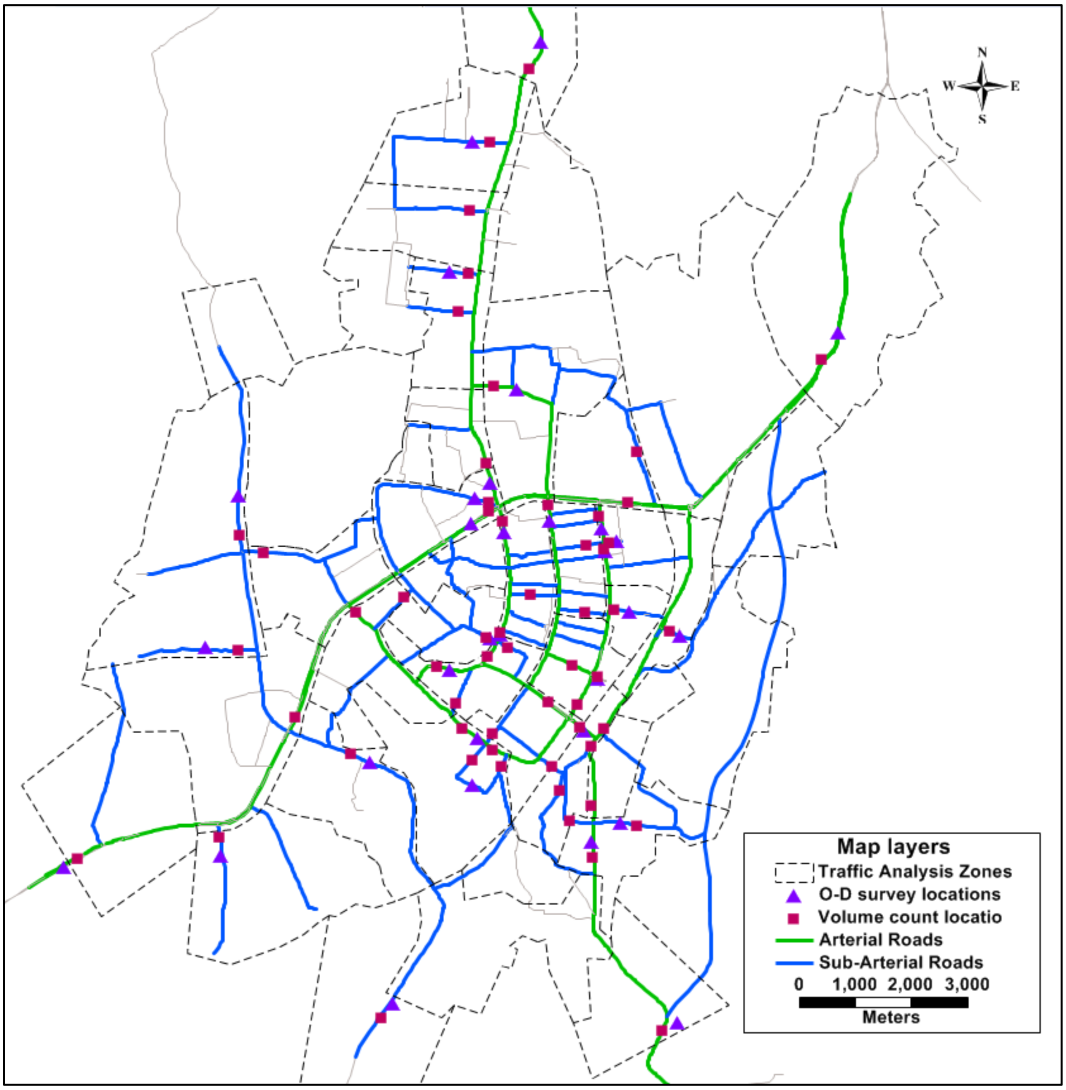

Fig. 4. Data Collection Locations

Volume studies were conducted at all the 57 locations for a duration of 16 hours (6:00 a.m. to 10:00 p.m.) using videographic surveys. Later, mode-wise traffic counts on these links were extracted from the video data. The O-D surveys were also conducted simultaneously at 25 locations to obtain a sample O-D pattern of the study area. These 25 locations were selected judiciously to capture maximum trip information while considering the safety and feasibility of roadside surveys. Around 35,000 road users were intercepted at roadside during the O-D surveys. From the volume surveys, it was observed that the traffic composition was highly dominated by motorized two-wheelers followed by car. Therefore, it was necessary to estimate the O-D matrix of these two modes simultaneously to incorporate the congestion effect. The mode-wise O-D matrices (each 43x43) estimated based on the O-D survey were used as seed matrices for the estimation of mode-wise final O-D matrices.

5. Analysis and Results

This section includes the outcomes of the study with regards to (i) variations in selection sets chosen by experts (ii) estimation of O-D matrices and (iii) comparison of estimated O-D matrices

5.1. Variation in selection sets chosen by experts

To understand the variation in the selection set of links for traffic counts by different experts, their responses were compared. The set of 45 links each selected by experts were not identical. Out of 45 links selected by each expert 32 links were found common across all the selection sets. The similarity among any two selection sets ranged between 80% - 88 %. A further investigation revealed that the common links selected by the experts are mainly the primary links such as (i) all the entry and exit links (contribute to trip information corresponding to external zones) (ii) major arterial roads (connect larger number of O-D pairs in the city and thereby, maximizes the information obtained from the link counts), and (iii) links connecting major points of interest and major intersections in the study area (provide information regarding highly important O-D trips in the network). The differences in selection sets were essentially observed in the sub-arterial roads. Each sub-arterial link provides information involving only a few TAZs; these are useful to enhance the structure of O-D matrix. The differences in selection of sub-arterials maybe attributed to selection of a small subset from a high number of sub-arterial links, multiple combinations of links resulting in similar information, and difference in perception across experts to enhance the O-D matrix. Therefore, it can be inferred that while deciding the selection sets for traffic link counts the experts mostly include the primary links (which contribute majorly to the O-D pattern structure of the network) and deviations are mostly observed in the selection of sub-arterial roads. The selection sets of the five experts based on number of arterials and sub-arterials are summarized in Table 3. The similarity (in terms of number of links) across the selection sets is reported in Table 4. The similarity among any two selection sets for arterial roads ranged between 72% - 84 %, while for sub-arterials roads it was found to be in the range of 50%-65%. The Fig. 5 illustrates an example by comparing the selections sets of expert 1 and expert 2.

Table 3 Number of Arterial and Sub-Arterial links selected by experts

	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5
Arterials	21	23	20	22	21
Sub-arterials	24	22	25	23	24

Table 4 Pairwise similarity in number of Arterials (A) and Sub-Arterials (SA) selected by experts

	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5
Expert 1					
Expert 2	A- 21, SA -16				
Expert 3	A- 18, SA- 21	A- 20, SA-20			
Expert 4	A- 20, SA-19	A- 21, SA-19	A- 18, SA-19		
Expert 5	A- 20, SA- 18	A- 19, SA-19	A- 18, SA-21	A- 20, SA-20	

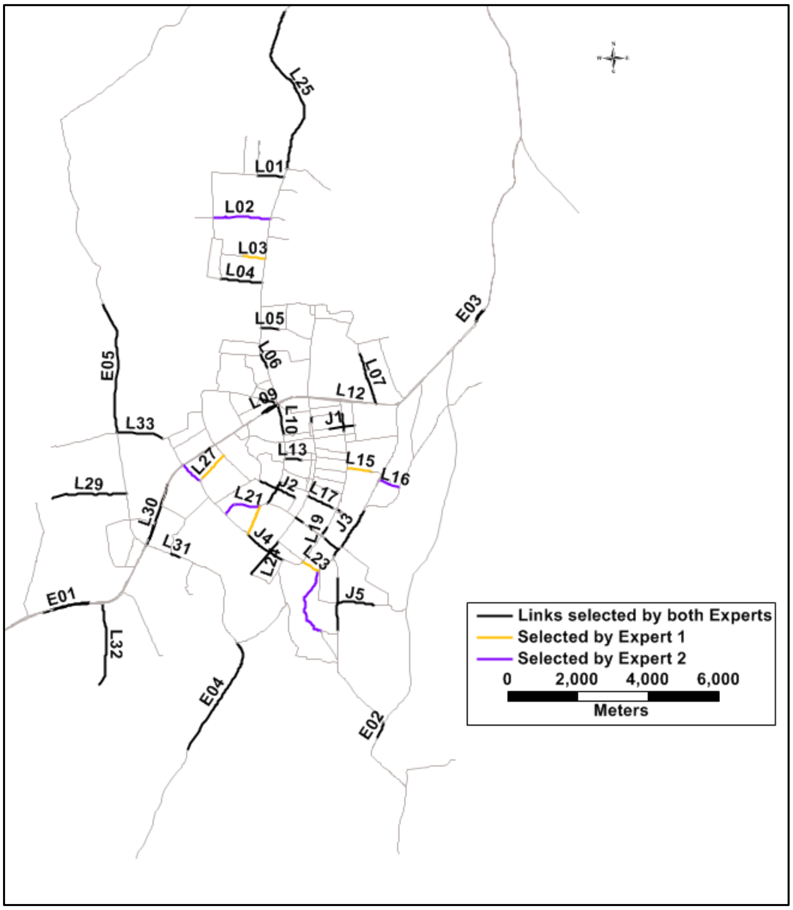

Fig. 5 Comparison of links selected by Expert 1 and Expert 2

5.2. *Estimation of O-D matrices*

As discussed in section 3.2, the Nielson's MPME approach was used for estimating the mode-wise O-D matrices from different selection sets of link counts. The modes considered for the present study were car and motorized two-wheelers (MTW). Passenger car units (PCU) value of 0.75 was assigned for motorized two-wheelers (IRC, 1990). Additionally, to consider the impact of other modes such as public and paratransit modes, their flow values were preloaded onto the network. Mode-wise seed O-D matrix and mode-wise traffic counts were assigned to the network. Link information such as flow, capacity, and travel time were also associated with the model. Any zero value cells in the seed matrix would not get updated and remain zero. Therefore, between few O-D pairs where trips were expected a positive value (one) was assigned, in place of the initial zero and matrix was estimated. Multiple iterations (maximum 300) were performed until the observed flow and estimated flow values converged.

O-D matrices were estimated for five selection sets. For estimation of mode-wise O-D matrices, the set of 45 links selected by the respective expert was used as input or calibration links, and remaining ten links for which link counts are available were used as validating links (total 57 unique link counts are available from the volume survey). For example, in Trial 1, the mode-wise links counts of 45 links selected by expert 1 were used as input for estimating mode-wise O-D matrices, and the remaining links were used for validation.

The average and maximum difference between the actual and estimated flow values for car and motorised two-wheelers for calibration and validation links are shown in Table 5. The values are within the acceptable limit of 10% (Almasri and Al-Jazzar, 2013). All results obtained from the five different input set of links selected by different experts are under the acceptable limit so all the obtained matrices are potential solutions.

Table 5. Average and maximum errors of link volumes of cars and motorized two-wheelers (MTW) (in percentage)

	Average Error				Maximum Error			
	Calibration		Validation		Calibration		Validation	
	Car	MTW	Car	MTW	Car	MTW	Car	MTW
Trial 1	5.26	5.82	8.16	7.89	21.92	20.48	26.13	25.15
Trial 2	5.85	6.29	7.16	8.18	19.65	20.48	26.14	27.35
Trial 3	5.43	6.12	9.01	7.98	19.26	20.48	23.58	21.76
Trial 4	6.05	6.61	8.12	8.16	24.65	20.48	31.23	27.07
Trial 5	5.67	6.47	8.14	6.92	20.06	20.48	27.05	26.21

5.3. *Comparison of estimated O-D matrices*

To understand the influence of the selection set on the estimated O-D matrix, initially mode-wise O-D matrices were estimated with respect to each set of links selected by experts and then a pairwise comparison of the estimated O-D matrix was performed.

Total Demand Deviation (TDD) % is used to check the difference in total trip information. The results are summarized in the following Table 6 for car and Table 7 for motorized two-wheelers. The maximum difference between any selection sets is 1.58%, which indicates that selection sets most likely did not have impact on overall trip information.

Table 6. Car TDD (in percentage)

	ODM1	ODM2	ODM3	ODM4	ODM5
ODM1	0.00				
ODM2	0.14	0.00			
ODM3	1.44	1.58	0.00		
ODM4	0.15	0.29	1.29	0.00	
ODM5	0.21	0.35	1.22	0.06	0.00

Table 7. Motorised two-wheelers TDD (in percentage)

	ODM1	ODM2	ODM3	ODM4	ODM5
ODM1	0.00				
ODM2	0.31	0.00			
ODM3	0.96	1.28	0.00		
ODM4	0.15	0.16	1.11	0.00	
ODM5	0.09	0.23	1.05	0.07	0.00

In addition to TDD, the Wilcoxon signed-rank test statistics was used to test the matrices for any difference in the O-D pattern using individual O-D pair. The results are summarised in Table 8 and Table 9. Interestingly, some significant difference was observed in a few cases at 95 % level of significance (α= 0.05). This indicates that selection set influences the O-D pattern even though the overall trips remained similar. Although all the selection sets have resulted in an acceptable O-D estimation, it is interesting to note that a difference is O-D pattern can be observed. Considering the results it was observed while overall trip information remained similar for the different selection sets, it was likely that they influenced the O-D patterns.

Table 8. Car - Wilcoxon signed-rank test Statistics (significance value)

	ODM1	ODM2	ODM3	ODM4	ODM5
ODM1	0				
ODM2	.567	0			
ODM3	.059	.621	0		
ODM4	**.002**	.118	.654	0	
ODM5	**.026**	**.016**	.371	.107	0

Table 9. Motorised Two-Wheelers - Wilcoxon signed-rank test statistics (significance value)

	ODM1	ODM2	ODM3	ODM4	ODM5
ODM1	0				
ODM2	.234	0			
ODM3	**.022**	.497	0		
ODM4	.230	.891	.325	0	
ODM5	.346	.229	**.024**	.145	0

In previous studies, an estimated O-D matrix is considered acceptable when average error on the validation links is within the tolerance limit (10%) (Almasri and Al-Jazzar, 2013). In the present study, matrices estimated from all five different selection sets resulted in acceptable errors when assigned on the network. However, the average and maximum errors of assigned link volumes (Table 5) varied across the different O-D matrices estimated. Considering that pairwise comparison of the estimated matrices indicated their statistically significant difference, the variation in average and maximum errors can be judiciously used to determine a superior link selection set and thereby an appropriate O-D matrix. In addition, it should be stressed that O-D matrix estimated using a single set of links can be evaluated only based on the threshold for acceptable average error in the absence of a reference and target matrix. However, when multiple set of links are used as inputs the estimated matrices may be compared based on the average and maximum errors of assigned link volumes in addition. This clearly illustrates the advantage of considering multiple link selection sets over a single link selection set for O-D matrix estimation.

The O-D matrices estimated using the five selection sets were assigned to the network for comparing the average error for all 57 links (calibration and validation links). The results are presented in Table 10. Based on the average error, none of the five selection sets were optimal for both car and motorized two-wheeler (MTW). The matrix estimated from selection set 1 produced better result for car while selection set 3 produced better result for MTW. In such cases, a final selection could be made by giving due consideration to maximum error. In the present case, mode-wise O-D matrices estimated from selection set 3 (trial 3) can be considered as a solution as it has least average error for MTW (second best for car) and also least maximum error for both car and MTW among the five.

Additionally, a mean O-D matrix of five estimated O-D matrix is also assigned on the network and the performance in terms of average and maximum error on the links is used to compare with the five estimated matrices. Interestingly the mean O-D matrix resulted in the least average error for car, marginally second least for MTW and least maximum error for both car and MTW in comparison with all the estimated O-D matrices. Therefore, the mean O-D matrix can be used as the final O-D matrix.

Table 10. Average and maximum error of all links in percentage (%)

	Average Error		Maximum Error	
	Car	MTW	Car	MTW
Trial 1	**5.96**	6.51	26.13	25.15
Trial 2	6.08	6.63	26.14	27.35
Trial 3	6.07	**6.45**	23.58	21.76
Trial 4	6.42	6.89	31.23	27.07
Trial 5	6.11	6.55	27.05	26.21
T_{mean}	**5.83**	6.48	**22.13**	**20.57**

6. Conclusion:

The present study brought out several interesting findings in the context of O-D matrix estimation using link counts and a sample O-D matrix. In such works usually observed traffic counts on only one set of links selected by the expert(s) is used as input for estimation of O-D matrix. In the context of present study the set of links selected by five experts were found to vary. The variation was predominant for lower order links (sub-arterials) which are relatively large in number in a city as compared to higher order links (arterial roads). The O-D matrices estimated based on different input links selected by experts were found to be statistically significantly different in some cases. This clearly indicates that estimating O-D matrix based on one set of links selected heuristically by expert(s) may not be rational, highlighting the need for rethinking in selection of links.

It is difficult to judge the quality of O-D matrix without any reference/target matrix. Therefore, the quality of matrix is assessed based on the performance when assigned on the network. As the O-D matrix estimated is sensitive to the link selection, it is more rational to estimate multiple O-D matrices based on different set of links selected and select an O-D matrix which minimizes the errors in link flows when assigned on the network. When O-D matrix is estimated for multiple modes simultaneously, it may happen (as observed in this study) that no single selection is best across the modes. In such cases, the maximum error in addition to average error may also be considered while making the decision. Additionally, it may also be beneficial to compare the performance of a representative O-D matrix (such as mean O-D matrix) with respect to the average and maximum errors before deciding the final O-D matrix. Altogether the findings indicate that the selection of links and resultant matrices vary significantly depending on the expert. Thus the study infers that for any given network, it is advisable to consider multiple selection set of links, estimate corresponding O-D matrices and subsequently select the O-D matrix based on the errors when assigned on the network. Although the results and observations are case specific, the findings reported in the work are expected to be of interest to transport planners who are working on development of O-D matrix from link counts in other cities.

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