ARCHIVES OF TRANSPORT
Volume 53, Issue 1, 2020

ISSN (print): *0866-9546*
e-ISSN (online): *2300-8830*
DOI: *10.5604/01.3001.0014.1743*

IMPACT ASSESSMENT OF SHORT-TERM MANAGEMENT MEASURES ON TRAVEL DEMAND

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Abstract:

Travel Demand Management (TDM) can be considered as the most viable option to manage the increasing traffic demand by controlling excessive usage of personalized vehicles. TDM provides expanded options to manage existing travel demand by redistributing the demand rather than increasing the supply. To analyze the impact of TDM measures, the existing travel demand of the area should be identified. In order to get quantitative information on the travel demand and the performance of different alternatives or choices of the available transportation system, travel demand model has to be developed. This concept is more useful in developing countries like India, which have limited resources and increasing demands. Transport related issues such as congestion, low service levels and lack of efficient public transportation compels commuters to shift their travel modes to private transport, resulting in unbalanced modal splits. The present study explores the potential to implement travel demand management measures at Kazhakoottam, an IT business hub cum residential area of Thiruvananthapuram city, a medium sized city in India. Travel demand growth at Kazhakoottam is a matter of concern because the traffic is highly concentrated in this area and facility expansion costs are pretty high. A sequential four-stage travel demand model was developed based on a total of 1416 individual household questionnaire responses using the macro simulation software CUBE. Trip generation models were developed using linear regression and mode split was modelled as multinomial logit model in SPSS. The base year traffic flows were estimated and validated with field data. The developed model was then used for improving the road network conditions by suggesting short-term TDM measures. Three TDM scenarios viz; integrating public transit system with feeder mode, carpooling and reducing the distance of bus stops from zone centroids were analysed. The results indicated an increase in public transit ridership and considerable modal shift from private to public/shared transit.

Keywords: *travel demand management, four stage model, linear regression, modal shift, multinomial logit model*

To cite this article:

D'Cruz, J. J. M., Alex, A. P., Manju, V. S., Peter, L., 2020. Impact assessment of short-term management measures on travel demand. Archives of Transport, 53(1), 37-52. DOI: https://doi.org/10.5604/01.3001.0014.1743

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1. Introduction

Urban development and its related settlements are mostly connected to road transport planning and investments. A critical problem in most developing countries like India is the inadequacy of transport infrastructure, which is aggravated by increasing demands for intra city travel due to rapid growth in both population and employment. Poor mobility ruins several man hours in traffic congestion, road accidents, low speed, heavy vehicle density etc. This condition demands better planning and management of transportation facilities in a country. There is an enormous rise in the use of personalized modes due to increase in travel demand as well as commuter's preference for personal comfort and convenience. These personalized vehicles will further cause deterioration in traffic and environmental conditions. This necessitates a travel mode shift from personalized vehicles like car to sustainable modes like walk/cycle for short trips and to public transport for long trips. In this scenario, Travel Demand Management (TDM) can be considered as the most viable option to manage the increasing traffic demand by controlling excessive usage of personalized vehicles.

Travel Demand Management takes advantage of the possibility of redistributing existing traffic demand by utilizing available infrastructure and facilities. With limited resources to devote for transportation infrastructure, TDM measures can offer more efficient transport solutions for people and goods which will help to ease the pressure on our congested roads, and make the whole sector more environmental friendly, safer, and cost efficient. In this respect, Travel Demand Management will help to bring about a truly sustainable and effective transport system. To analyze the impact of TDM measures, the existing travel demand of the area should be identified. In order to get quantitative information on the travel demand and the performance of different alternatives or choices of the available transportation system, travel demand model has to be developed.

The major focus of this study is to carry out methodological analysis to develop and execute transport modelling and apply travel demand management measures using the macro-simulation software CUBE. A travel demand model was developed for Kazhakoottam, an IT business hub of Kerala in India, using the conventional four stage method. Travel demand growth at Kazhakoottam is a matter of concern because the traffic is highly concentrated in this area and facility expansion costs are pretty high. The developed model was then used for improving the road network conditions by suggesting short-term TDM measures. Three travel demand management measures were analysed, viz; providing feeder modes to public transportation, carpooling and providing bus stops at less than 400 m from zone centroids. Improving alternative modes against personal modes and applying travel demand management measures would be the most cost-effective way to improve transportation at Kazhakoottam.

2. State of the Art

The most commonly cited objectives of TDM measures are efficiency in the use of resources; improved accessibility; environmental protection; and increased safety. Different possibilities should be considered to reach these objectives, which includes giving priority to public transit and non- motorized modes, providing feeder modes to public transportation, taxi share/ bike share, parking policies and pricing, fuel pricing etc.

Four stage Urban Transportation Modelling System (UTMS) with trip generation, trip distribution, mode split and trip assignment continues to be the widely used method for simulating traffic volumes on transport networks in the planning of urban transportation systems (Kadiyali et al., 2009; Sheppard, 1995; Meyer et al., 2000). Trip generation modelling can consider either household as the unit of analysis (Badoe et al., 2004) or person- category model of trip generation (Supernak et al., 1983). The techniques generally used for trip generation modelling are cross classification, multiple regression analysis and trip rate analysis models (Ortuzar et al., 2001). McNally (2000) studied the conventional model of four stage travel forecasting and carried out trip generation modelling by classifying trips into three; Home based Work (HBW), Non-Home Based (NHB) and Home Based Other (HBO) trips. Various factors which affect the trip generation are land use, vehicle ownership, income, household size, density and type of development, availability of public transportation, and the quality of the transportation system, among other factors that represent the TAZs (Lane et al., 1973; Papacostas et al., 2001).

The trip distribution follows a gravity approach, which is widely used and fully meets the requirements of an up-to-date demand model (Mounir et al., 2014; Berki et al., 2017; Mehta et al., 2017). The friction factors can be provided as a look up table with a corresponding factor for each travel (NCHRP Report 365). Wilson (1998) studied the interaction between land use pattern and transportation network development. Trip distribution is mainly affected by the purpose of the trip, weight of each zone as well as the impedance between zones (Roy et al., 2003; Simini et al., 2012). Different trip distribution models were developed over past decades with greater accuracy. Machine Learning (ML) techniques like decision trees and random forests (Ghasri et al., 2017), support vector machine (Karim et al., 2019), neural networks (Pourebrahim et al., 2019), fuzzy logic, genetic algorithm (Kalica et al., 2003) and advanced data collection techniques were also applied in various scenarios.

Mode decision is constrained by factors such as vehicle ownership, availability of public transit, transit fare and personal/household-level factors (Pendyala, 2009; Cirill et al., 2010; Pendyala et al., 2005). The majority of travel mode choice studies have been focused on econometric theory of random utility maximization. It assumes that an individual's choice is determined by the indirect utility of each alternative and the individual can choose the one that maximizes her/his utility level (Xiong et al., 2015). Various mode choice models were developed based on discrete choice models (Koppelman, 1983; McFadden et al., 2000; Hess et al., 2011) and its derivatives (Kitamura, 1990; Pendyala et al., 2000; Wainaina, 2003; Afandizadeh et al., 2010). Data mining methods and artificial intelligence were also employed to model behavioral process (Pendyala et al., 1998; Arentze et al., 2004; Xiong et al., 2013; Goulias, . 1999; Ben-Akiva, 2010; Choudhury et al., 2010, Alex et al., 2019).

The various types of traffic assignment models available are incremental assignment, all-or- nothing assignment (AON), user equilibrium assignment (UE), capacity restraint assignment, stochastic user equilibrium assignment (SUE) and dynamic assignment. Many studies have been conducted in trip assignment problems (Kumar et al., 2014; Noekel et al., 2009; Herawati, 2011; Paul, 2011). With this four-stage modelling, base traffic model can be developed. TDM measures will be applied and analyzed on the base traffic model to assess its impact.

The effectiveness of TDM measures in developing countries depends on many factors (Broaddus et al., 2009; Mahmood et al., 2009; Garling et al., 2007; Alonso et al., 2010; Vedagiri et al., 2009). Carpooling is a TDM measure which offers multiple benefits like congestion mitigation, reduced air and noise pollution, economic benefits, environmental benefits etc (Dewan et al., 2007; Suresh, 2016; Chintakayala et al., 2010) Most of the public policies often do not pay attention to long-term impacts on land use pattern and travel behavior. TDM supports public policy decisions to plan long and short-term transportation solutions more effectively.

3. Study Area and Data collection

The study area selected is Kazhakoottam ward of Thiruvananthapuram city, in the Kerala State; India. Kazhakoottam is an IT business centre cum residential area of Thiruvananthapuram city. This ward has a greater significance because the Technopark is located in this area. Technopark houses over 400 companies, providing jobs to over 58000 professionals and is still expanding with Technocity near Pallipuram. This can highly contribute to large number of trip attractions. Moreover, the Vikram Sarabhai Space Centre and Greenfield International Stadium are located in this area. In addition to its commercial activity, the growing population also demands provision of new traffic solutions which would handle future travel demand without controlling or regulating land use and economic growth.

The defined study area was divided into 13 Traffic Analysis Zones (TAZs), which includes 8 internal zones (Fig. 1) and 5 external zones. The total population of Kazhakoottam ward area in 2011 was 36,264 based on Census Data 2011. The projected population of this area for the year 2019 is 42,792. The rapid growth of population and commercial activities in the area affects the traffic condition in a worst manner. During the peak hours, the area is witnessing severe congestion and longer travel time. The increasing travel demand at Kazhakoottam is a matter of concern because facility expansion costs in the area is pretty high. TDM measures would be the most cost-effective way to improve transportation facilities in such a situation because it redistributes the traffic demand without insisting infrastructure supply.

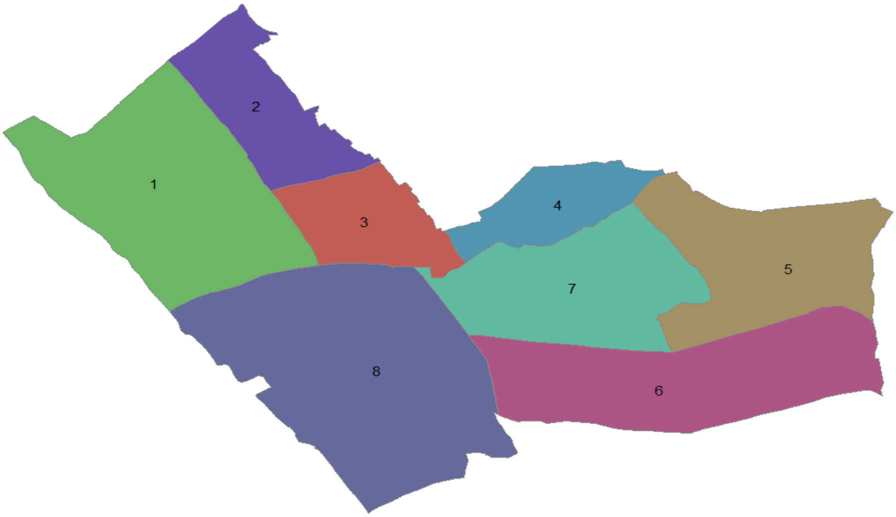

Fig. 1. Internal Zones

Data collected for this study includes socio-economic, employment, road inventory, highway network characteristics, land use and Origin-Destination data. Socio-economic data was collected by home interview survey. The main objective was to collect household information, personal information and activity- travel information. Household information included location of the household, type of dwelling unit, household size and vehicle ownership. Personal information included gender, age, occupation, type of employment, place of occupation and monthly income. The gender wise distribution of the sample data collected shows that the study area has almost equal distribution of male and female population. About 34% of the population falls under the age group of 26-45, of which majority were workers. 35% of the population have full time job. Vehicle ownership details showed that 46% of households had two wheelers followed by 32% having four wheelers. These two modes contribute a major share of the vehicle distribution. Activity-travel information consists of the activities and trips made by each individual of the household. It includes the origin, destination, mode of travel, travel cost, travel distance, travel time, frequency of trips, trip purpose, vehicle ownership and their willingness to shift to public/ shared transit modes. Data were collected for selected households in each zone and a total of 1461 samples were taken. Employment data were collected by classifying the buildings in the study area under five categories as shown in Table 1.

Table 1. Employment Category

Category	Type of Buildings
Type 1	Government/Private offices
Type 2	Hotels and restaurants
Type 3	Shops
Type 4	Educational institutions
Type 5	Places of worship, other recreational centres

Road inventory survey was conducted to assess the physical condition and characteristics of roads within the study area, so as to identify traffic bottlenecks and constraints. It assesses potential capacity and identifies the extent for future development. Road inventory data included the details about the road network such as length, lane width, shoulder width, number of lanes, one way/two-way, parking availability and median type. The highway network characteristics collected for the study included traffic speed, traffic volume counts and capacity of road links. Video-graphic method was adopted and the traffic flows obtained were converted into equivalent Passenger Car Units (PCU) by using conversion factors as suggested by Indian Roads Congress, IRC SP 41.

4. Travel Demand Modelling

Travel demand modelling using CUBE software was done which consists of network formation and four stage model development. Each stage is discussed in the following subsections.

4.1. Network formation

The road network and traffic analysis zone map were digitalized using ArcGIS and QGIS Software. The highway network thus created was converted to .NET file in CUBE software and all the necessary link attributes were assigned to it. The socio-economic data which include household data and employment data for the study area were organized into the Traffic Analysis Zones or TAZs. The digitized road network in Arc GIS is shown in Fig. 2, in which all major roads are included.

4.2. Trip generation

The production and attraction values for the study area were estimated for three different trip categories, viz., Home-Based Daily (HBD) trips, Home-Based Other (HBO) trips and Non-Home-Based (NHB) trips. The trip production and attraction models were developed using Multiple Linear Regression (MLR).The trip production and attraction models obtained are given in Table 2 and 3 respectively. These trip generation models, along with zonal data and total external-internal trips, were given as input to obtain trip end matrix. CUBE script used is shown in Fig.3.

The output of the trip generation step was the trip ends in each zone by trip category as given in Table 4. The values in each cell represent the number of trips produced and attracted for all the three trip categories in the study area. The total trip ends are shown in Table 5. It shows that maximum number of trip productions is from Zone 8.This is due to the fact that the IT centre, Technopark is located in this zone and it is attracting maximum number of trips. It is also found that maximum number of attractions is from the same zone.

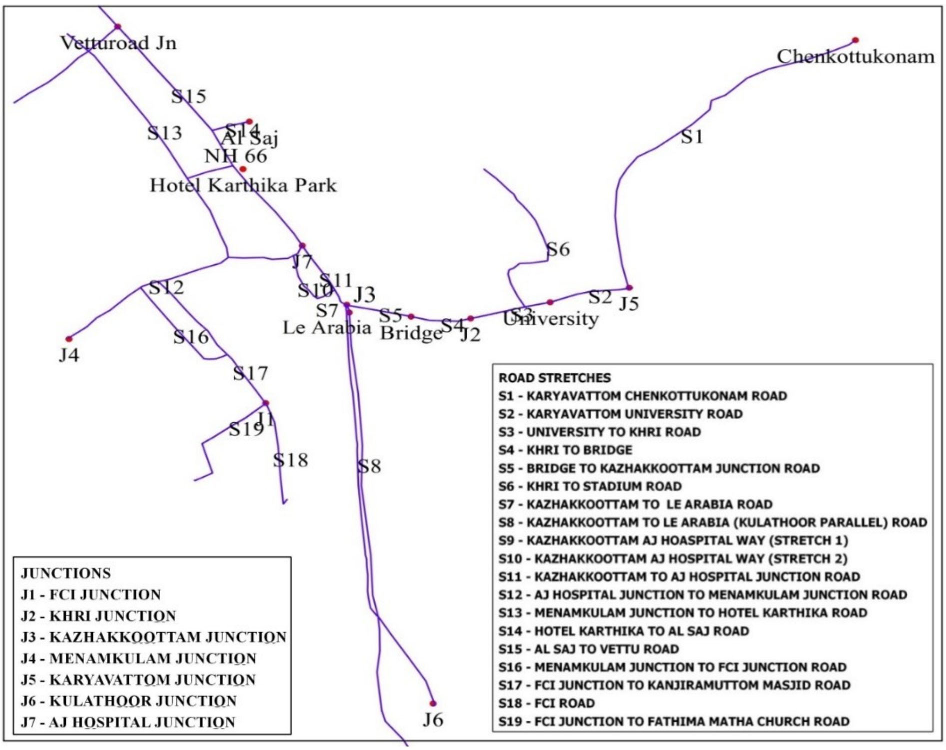

Fig. 2 Digitized Road Network in Arc GIS

Table 2. Trip production Models

Production Equations	**Adj. R^2**
HBD= -5.538 + 1.003 Age $_{(20\text{-}55)}$ + 1.587 HH_2 + 0.382 HH_3-2.048 $HH_{>3}$	0.987
HBO= 28.138 - 12.687 Age $_{<5}$ + 1.466 $Age_{>55}$ +2.722 $HH_{>3}$-0.271 Age $_{20\text{-}55}$	0.799
NHB = -0.724-0.357 HH_2-0.409 Age $_{5\text{-}20}$ +0.662 TWavailability	0.746

where:

$Age_{<5}$ = Persons with age group less than 5,
$Age_{5\text{-}20}$ = Persons with age group 5 to 20,
Age $_{20\text{-}55}$ = Persons with age group 20 to 55,
$Age_{>55}$ = Persons with age group greater than 55,
HH_2 = Household having only 2 members,
HH_3 = Household having only 3 members,
$HH_{>3}$ = Household having greater than 3 members,
TW_avail = Two-wheeler availability

Table 3. Trip Attraction Models

Attraction Equations	**Adj. R^2**
HBD= 20.867+ 7.771 Type1+ 5.661 Type4+ 2.019 Type3	0.878
HBO= 20.085+ 7.473 Type1+ 2.741 Type3	0.834
NHB = 0.231+0.438 Type1+1.723 Type2+0.974 Type5	0.921

where:

Type1 to type 5 are the employment categories as given in Table 1.

```
RUN PGM=GENERATION PRNFILE="C:\Users\Jini\Desktop\Thesis\Cube_files\TMGEN00A.PRN"
MSG='Trip Generation'
FILEI ZDATI[2] = "C:\Users\Jini\Desktop\Thesis\External trips\EItrips (1).dbf"
FILEI ZDATI[1] = "C:\Users\Jini\Desktop\Thesis\Cube_shpfiles\zone\ZONESHP.dbf"
FILEO PAO[1] = "C:\USERS\JINI\DESKTOP\THESIS\CUBE_FILES\TRIPENDS.DAT",

FORM=6.0, DBF=T, LIST=Z, P[1] P[2] P[3] P[4]  A[1] A[2] A[3] A[4]
;DBF: Z=zone field name
;TXT: Z=zone field location, var=field location, var=field location ....
PARAMETERS ZONES = 13

PROCESS PHASE=ILOOP
 IF (I<=8)
;calculate productions by purpose
P[1] = -5.538+1.587*zi.1.HH_2+1.003*zi.1.Age20to55+0.382*zi.1.HH_3-2.048*zi.1.HH>3
P[2] = 28.138-12.687*zi.1.Age<5+1.466*zi.1.Age>55+2.722*zi.1.HH>3-0.271*zi.1.Age20to55
P[3] = 0.724-0.357*zi.1.HH_2-0.409*zi.1.Age5to20+0.662*zi.1.TWavailability
;calculate attractions by purpose
A[1] = 20.867+7.771*zi.1.Type1+5.661*zi.1.Type4+2.019*zi.1.Type3
A[2] = 20.085+7.473*zi.1.Type1+2.741*zi.1.Type3
A[3] = 0.231+0.438*zi.1.Type1+1.723*zi.1.Type2+0.974*zi.1.Type5
ELSE
P[4] =  1*zi.2.eitrips
  ENDIF
ENDPROCESS
;adjust zonal attractions so total attractions match total productions
 PHASE=ADJUST
A[1] = P[1][0]/A[1][0] * A[1]  ; adjust a's to match p's
A[2] = P[2][0]/A[2][0] * A[2]
A[3] = P[3][0]/A[3][0] * A[3]
    A[4]=(P[4][0]*(A[1]+A[2]+A[3])/(A[1][0]+A[2][0]+A[3][0]))
ENDPROCESS

ENDRUN
```

Fig.3 Trip generation script in CUBE network

Table 4. Trip Ends before Balancing

Zones	Production			Attraction		
	HBD	HBO	NHB	HBD	HBO	NHB
1	2824	934	256	3001	1036	221
2	1860	2185	170	1720	2048	234
3	2094	1151	204	2103	988	216
4	1627	1446	165	1576	1294	198
5	1499	1186	233	1796	1003	185
6	2061	948	336	2123	1123	322
7	3169	1959	278	3078	2234	226
8	3247	2423	400	2987	2507	440

Table 5. Total trip ends

Sl No.	Trip Types	Total Trip Ends
1	HBD Trip Productions	18,382
2	HBO Trip Productions	12,233
3	NHB Trip Productions	2042
4	HBD Trip Attractions	20,245
5	HBO Trip Attractions	10,482
6	NHB Trip Attractions	3002

4.3. Balancing trip ends

The trip productions and attractions should be balanced before the trip distribution stage as there should be only two ends of a trip. The trip attractions were adjusted so that total productions and attractions are equal. The factor for balancing was calculated using the equations (1) to(3) . The balanced trip ends obtained is shown in Table 6.

$$\text{Factor} = CTp\sum A_z \quad (1)$$

where:

$$CTp = \sum P_z + \sum P_E - \sum A_E \quad (2)$$

$$A_Z' = \text{Factor} \times A_Z \quad (3)$$

A_Z = Trip attractions at each zone (by purpose)
CTp = The total of productions
P_z = Trip productions for each zone
P_E = Trip productions at each external station
A_E = Trip attractions at each external station
A_Z' = Balanced Trip Attractions

P1, P2 and P3 represents trip productions and A1, A2, A3 represents trip attractions for the three trip categories HBD, HBO and NHB. P4 and A4 represent trip ends for external trip purposes. The values in each cell represent balanced trip production and attraction numbers in each zone. Total balanced productions and attractions were obtained as 32,657.

Table 6. Trip Ends after Balancing

Z	P1	P2	P3	P4	A1	A2	A3	A4
1	2824	934	256	0	3141	963	254	1073
2	1860	2185	170	0	1764	2131	204	1009
3	2094	1151	204	0	2195	1141	198	870
4	1627	1446	165	0	1484	1424	175	759
5	1499	1186	233	0	1656	1135	224	742
6	2061	948	336	0	2079	972	318	829
7	3169	1959	278	0	2978	2034	249	1295
8	3247	2423	400	0	3087	2433	420	1462
9	0	0	0	834	0	0	0	0
10	0	0	0	1913	0	0	0	0
11	0	0	0	1704	0	0	0	0
12	0	0	0	936	0	0	0	0
13	0	0	0	2652	0	0	0	0

4.4. Trip distribution

In the trip distribution step, the trips generated from each TAZ were allotted to all other TAZs in the study area. Doubly constrained gravity model was used for developing the trip distribution model. The gravity model is given in equation (4):

$$T_{ij} = P_i \times \frac{A_i F_{ij} K_{ij}}{\sum_{j=0}^{n} A_j F_{ij}} \quad (4)$$

where:
T_{ij} = No. of trips from zone i to zone j,
P_i= No. of trip productions in zone i,
A_j= No. of trip attractions in zone j,
F_{ij}= Friction factor relating to spatial separation between zone i&j,
K_{ij}= Trip distribution adjustment factor between zone i to zone j.

The inputs to the trip distribution include balanced trip end matrix obtained from trip generation stage, highway skim matrix and friction factors. The output matrix gave the number of trips distributed from one zone to another for all the trip purposes.

4.4.1. Skim matrix

The zone to zone skim matrix or travel impedance matrix is one of the important inputs to the trip distribution step. It represents the shortest path from one zone to another. The CUBE script for travel impedance matrix is shown in Fig. 4 and the skim matrix is shown in Table 7.

```
RUN PGM=HIGHWAY PRNFILE="C:\Users\Jini\Desktop\Thesis\Cube_files\TMEETRIPS00A.PRN"
MSG='Highway Network Skims'
FILEI NETI = "C:\USERS\JINI\DESKTOP\THESIS\CUBE_FILES\KAZHNEW.NET"
FILEO MATO[1] = "C:\USERS\JINI\DESKTOP\THESIS\CUBE_FILES\\HIGHWAY_SKIM.MAT",
MO=1-3, NAME=TIME,DISTANCE,COST
PROCESS PHASE=ILOOP
  PATHLOAD PATH=COST, CONSOLIDATE=T, MW[1]=pathtrace(TIME),
MW[2]=pathtrace(li.distance)/1000, MW[3] = pathtrace(COST)*0.1
    MW[1][I] = ROWMIN(1)*0.50  ; Intrazonal time
    MW[2][I] = ROWMIN(2)*0.50             ; Set Intrazonal Dist = 0
    MW[3][I]=ROWMIN(3)*0.50;
ENDPROCESS
PROCESS PHASE=ADJUST
FUNCTION COST = (0.5*LI.TIME)+(0.00151*li.distance)+ 5
ENDPROCESS
ENDRUN
```

Fig. 4. CUBE Script for Travel Impedance Matrix

Table 7. Skim Matrix

Zone	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
1	0.34	3.74	1.99	4.48	8.16	4.63	4.00	3.94	0.67	3.52	2.59	3.52	8.59
2	3.74	0.74	1.99	5.21	8.90	5.36	4.74	4.77	4.41	1.47	1.79	5.18	9.32
3	1.99	1.99	0.42	3.22	6.91	3.38	2.75	2.78	2.66	2.80	0.84	3.20	7.34
4	4.48	5.21	3.22	1.34	6.55	3.54	2.69	5.72	5.15	6.02	4.06	6.14	6.98
5	8.16	8.90	6.91	6.55	0.21	3.57	5.16	7.19	8.83	9.71	7.75	7.60	0.43
6	4.63	5.36	3.38	3.54	3.57	0.81	1.63	3.66	5.30	6.17	4.21	4.07	4.00
7	4.00	4.74	2.75	2.69	5.16	1.63	0.81	3.03	4.67	5.55	3.59	3.45	5.59
8	3.94	4.77	2.78	5.72	7.19	3.66	3.03	0.21	4.29	5.60	3.62	0.41	7.62
9	0.67	4.41	2.66	5.15	8.83	5.30	4.67	4.29	0.34	4.19	3.26	3.88	9.26
10	3.52	1.47	2.80	6.02	9.71	6.17	5.55	5.60	4.19	0.74	2.60	6.01	10.13
11	2.59	1.79	0.84	4.06	7.75	4.21	3.59	3.62	3.26	2.60	0.42	4.03	8.17
12	3.52	5.18	3.20	6.14	7.60	4.07	3.45	0.41	3.88	6.01	4.03	0.21	8.03
13	8.59	9.32	7.34	6.98	0.43	4.00	5.59	7.62	9.26	10.13	8.17	8.03	0.21

4.4.2. Friction factors

The friction factors are parameters used in the gravity model to account for travel time separation between zones. The friction factors attempt to show the effect of travel time or impedance on trip making. These factors were calculated using the gamma function given in equation (5). The values of a, b and c for initial friction factors are given in Table 8 (NCHRP Report 365)

$$F_{ij} = a \times t^{b} \times e^{ct} \tag{5}$$

where:
t = travel impedance (time in minutes)
a,b,c= model parameters

Table 8. Gamma Function Coefficients for Friction Factors

Trip Purpose	**a**	**b**	**c**
HBD	28507	-0.002	-0.123
HBO	139173	-1.285	-0.094
NHB	219113	-1.332	-0.100

The trip length frequencies obtained from the initial friction factors were compared with the observed trip frequencies from the OD survey. The calibrated friction factors considered are shown in Table 9 (NCHRP Report 365). The friction factors were adjusted until the trip length frequencies from the model matches the observed average trip length frequencies from the survey.

Table 9 Synthetic Friction Factors

Time (min)	HBD	HBO	NHB	Ext
1	25214	126632	196293	25214
5	14936	10979	15601	14936
10	7972	2811	37763	7972
15	4280	1041	1331	4280
20	2303	449	551	2303
25	1241	210	248	1241
30	669	104	118	669
35	361	53	58	361
40	195	28	30	195
45	105	15	15	105
50	57	8	8	57
55	31	4	4	31
60	17	3	2	17

4.4.3. Trip distribution process

The trip ends obtained from trip generation step and highway skim matrix obtained from the network, which is the measure of travel cost between each pair of zones in terms of time and distance and the friction factors were provided as the input to the CUBE software. The CUBE script for trip distribution is given in the Fig.5.

The output matrix in Table 10 shows the number of trips distributed from one zone to another for HBD trips. The trips were found decreasing as the distance between zones increases. The increased number of trips distributed in certain zones was due to increased activity in those particular zones.

```
RUN PGM=DISTRIBUTION
PRNFILE="C:\Users\Jini\Desktop\Thesis\Cube_files\TMGEN00B.PRN" MSG='Trip
Distribution'
;  ----- specify input p & a file and los file
FILEI ZDATI[1] = {PAI.Q},
Z=#1, P1=#2,P2=#3,P3=#4, P4=#5, A1=#6,A2=#7,A3=#8,A4=#8
FILEI MATI[1] = {MATI.Q}
FILEO MATO[1] = {MATO.Q},
MO=1-5,NAME={matnames}
   MAXITERS={maxiters},MAXRMSE={maxRMSE}
;  ----- setup friction factor lookup tables, input from file

   LOOKUP FILE = "{LOOKI.Q}",
 INTERPOLATE=Y, NAME=FF,
LOOKUP[1]=1,RESULT=2,
LOOKUP[2]=1,RESULT=3,
LOOKUP[3]=1,RESULT=4,
LOOKUP[4]=1, RESULT=5
;  ----- setup the working p's and a's
   SETPA P[1]=P1  A[1]=A1
   SETPA P[2]=P2  A[2]=A2
   SETPA P[3]=P3  A[3]=A3
   SETPA P[4]=P4  A[4]=A4
;  ----- get the los matrix into work matrix 10
MW[10] = MI.1.1
;  ----- do 4 gravity models, each followed by a frequency summation
   GRAVITY   PURPOSE=1, LOS=MW[10], FFACTORS=FF
   GRAVITY   PURPOSE=2, LOS=MW[10], FFACTORS=FF
   GRAVITY   PURPOSE=3, LOS=MW[10], FFACTORS=FF
   GRAVITY   PURPOSE=4, LOS=MW[10], FFACTORS=ff


MW[5] = MW[1] + MW[2] + MW[3] + MW[4]
{prt3} FREQUENCY VALUEMW=1  BASEMW=10,  RANGE=1-100
{prt3} FREQUENCY VALUEMW=2  BASEMW=10,  RANGE=1-100
{prt3} FREQUENCY VALUEMW=3  BASEMW=10,  RANGE=1-100
{prt3} FREQUENCY VALUEMW=4  BASEMW=10,  RANGE=1-100
;  ----- get a comparison report on last iteration
{prt2} REPORT ACOMP=1-4, ITERATIONS=99
ENDRUN
```

Fig. 5. CUBE Script for Trip Distribution

For example, the number of trips distributed to zone 8 was found to be more because it has a greater number of business centres. The trip length distribution curve was obtained for all the three trip categories and is shown in Fig. 6. The trip length frequency for HBD and HBO were obtained as 15 to 20 minutes and for NHB, it was 5 to 10 minutes.

Table 10. Trip Distribution for HBD trips

Zones	1	2	3	4	5	6	7	8
1	778	276	380	203	148	241	362	435
2	328	343	287	134	97	159	242	270
3	408	259	314	164	119	192	302	336
4	253	141	190	233	126	186	304	195
5	148	82	110	101	449	215	225	168
6	269	149	200	167	242	319	410	305
7	437	245	339	295	273	442	635	503
8	519	270	374	187	201	325	498	874

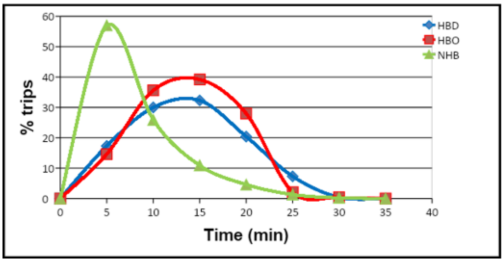

Fig. 6. Trip Length Frequency Distribution Curve

4.5. Modal split

In the third step, the mode split models were developed in the form of Multinomial Logit models. The modes considered for the study were car, two-wheeler, three-wheeler and bus. The total time taken for travel was considered as the independent variable and modes were taken as the dependent variables. Bus was considered as the reference category. The utility equations were developed in SPSS Software. The utility equations are given in equations (6), (7) and (8).

$$U(TW) = 0.506-0.032*time, \quad (6)$$
$$U(AUTO) = -1.265-0.075*time, \quad (7)$$
$$U(CAR)=-0.679-0.003*time \quad (8)$$

CUBE script for mode split is given in Fig. 7. The output of the mode split stage was in person trips by mode.

The OD matrix of the person trips by different modes such as car, two-wheeler, auto-rickshaw and bus were obtained. This was converted to vehicle trips by dividing with average occupancy factors for each mode. The average occupancy factors were taken from IRC-SP 30. The friction factors were adjusted until the trip length frequencies from the model matched the observed average trip length frequencies from the survey. The OD matrix of the person trips by different modes such as car, two-wheeler, auto-rickshaw and bus were obtained. This was converted to vehicle trips by dividing with auto occupancy factors for each mode. The auto occupancy factor used is given in Table 11. The obtained vehicle trips for each mode were multiplied with PCU values. The PCU values used for car, two-wheeler, three-wheeler and bus were 1, 0.5, 0.8 and 3.5. The final OD matrix in vehicle trips determined from this matrix is shown in Table 12.

Table 11. Average Occupancy Factors

Mode	Auto Occupancy Factor
Car	4.8
Two-Wheeler	1.5
Autorickshaw	1.76
Bus	43

Table 12. Final OD Matrix

Zones	1	2	3	4	5	6	7	8
1	668	164	282	120	75	130	194	242
2	191	886	316	99	51	98	151	179
3	300	298	281	108	62	104	212	253
4	144	101	120	519	74	117	306	124
5	76	47	60	67	737	133	135	101
6	145	95	108	107	138	366	425	181
7	229	151	226	294	150	439	686	358
8	281	177	266	119	110	188	356	1353

4.6. Trip assignment

All or nothing assignment technique was used to assign trips to the network in this study. It is assumed in this technique that the travel time on links does not vary with link flows. According to this method, a trip maker will choose that route which minimizes his/her travel time between a particular origin and destination pair. The input provided for this step was highway network and O-D matrix. CUBE script is shown in Fig.8. The travel time was chosen as path cost to assign trips. The trip assignment output, which is the volume count in each link is shown in Fig. 9. The congested links are shown as thick lines.

```
RUN PGM=MATRIX PRNFILE="D:\PROJ\TAMAT00B.PRN" MSG='Modal Split'
FILEI MATI[2] = "C:\USERS\JINI\DESKTOP\THESIS\CUBE_FILES\HIGHWAY_SKIM.MAT"
FILEI MATI[3] = "C:\USERS\JINI\DESKTOP\THESIS\CUBE_FILES\EXTERNALEX.MAT"
FILEI MATI[1] = "C:\USERS\JINI\DESKTOP\THESIS\CUBE_FILES\DIST.MAT"
FILEO MATO[1] = "C:\USERS\JINI\DESKTOP\THESIS\CUBE_FILES\MODECHOICE.MAT",
MO =6-10,
NAME = TW, BUS, AUTO, CAR,TOTAL
MW[1]=mi.1.HBD
MW[2]=mi.1.HBO
MW[3]=mi.1.NHB
MW[4]=mi.1.EI
MW[5]=mi.3.Trips

;Generalized utility of different modes

MW[26]=0.506-0.032*mi.2.1
MW[27]= -1.265-0.075*mi.2.1
MW[28]= -0.679-0.003*mi.2.1
MW[29]= 0

XCHOICE,
ALTERNATIVES= HBDCAR HBDTW HBDAUTO HBDBUS,
DEMANDMW = 1,
UTILITIESMW=26,27,28,29,
ODEMANDMW=30,31,32,33,
SPLIT = total HBDCAR HBDTW HBDAUTO HBDBUS,
STARTMW = 100

XCHOICE,
ALTERNATIVES= HBOCAR HBOTW HBOAUTO HBOBUS,
DEMANDMW = 2,
UTILITIESMW=26,27,28,29,
ODEMANDMW=34,35,36,37,
SPLIT = total HBOCAR HBOTW HBOAUTO HBOBUS,
STARTMW = 100

XCHOICE,
ALTERNATIVES= NHBCAR NHBTW NHBAUTO NHBBUS,
DEMANDMW = 3,
UTILITIESMW=26,27,28,29,
ODEMANDMW=38,39,40,41,
SPLIT = total NHBCAR NHBTW NHBAUTO NHBBUS,
STARTMW = 100

XCHOICE,
ALTERNATIVES= EICAR EITW EIAUTO EIBUS,
DEMANDMW = 4,
UTILITIESMW=26,27,28,29,
ODEMANDMW=42,43,44,45,
SPLIT = total EICAR EITW EIAUTO EIBUS,
STARTMW = 100

XCHOICE,
ALTERNATIVES= EECAR EETW EEAUTO EEBUS,
DEMANDMW = 5,
UTILITIESMW=26,27,28,29,
ODEMANDMW=46,47,48,49,
SPLIT = total EECAR EETW EEAUTO EEBUS,
STARTMW = 100
MW[6]=MW[30]+MW[34]+MW[38]; TW
MW[7]=MW[31]+MW[35]+MW[39]+MW[43]+MW[47] ; BUS
MW[8]=MW[32]+MW[36]+MW[40]+MW[44]+MW[48] ; AUTO
MW[9]=MW[33]+MW[37]+MW[41]+MW[45]+MW[49] ;CAR
MW[10]=MW[6]/4.8+MW[7]/3+MW[8]/2.2+MW[9]/12.28; TOTAL

ENDRUN
```

Fig. 7. CUBE Script for Mode Split

```
RUN PGM=HIGHWAY PRNFILE="C:\Users\Jini\Desktop\Thesis\Cube_files\KZHTA00B.PRN"
MSG='Trip Assignment'
FILEI NETI = {NETI.Q}
FILEI MATI[1] = {MATI.Q}
FILEO NETO = {NETO.Q}
PAR MAXITERS=1
PROCESS PHASE=ILOOP
PATHLOAD  PATH=COST, VOL[1]=MI.1.1    ; load trips
ENDPROCESS
PROCESS PHASE=ADJUST
function {
cost=(0.99*LI.TIME)+(0.00151*li.distance)+ 5
}
ENDPROCESS
ENDRUN
```

Fig. 8. CUBE Script for Trip Assignment

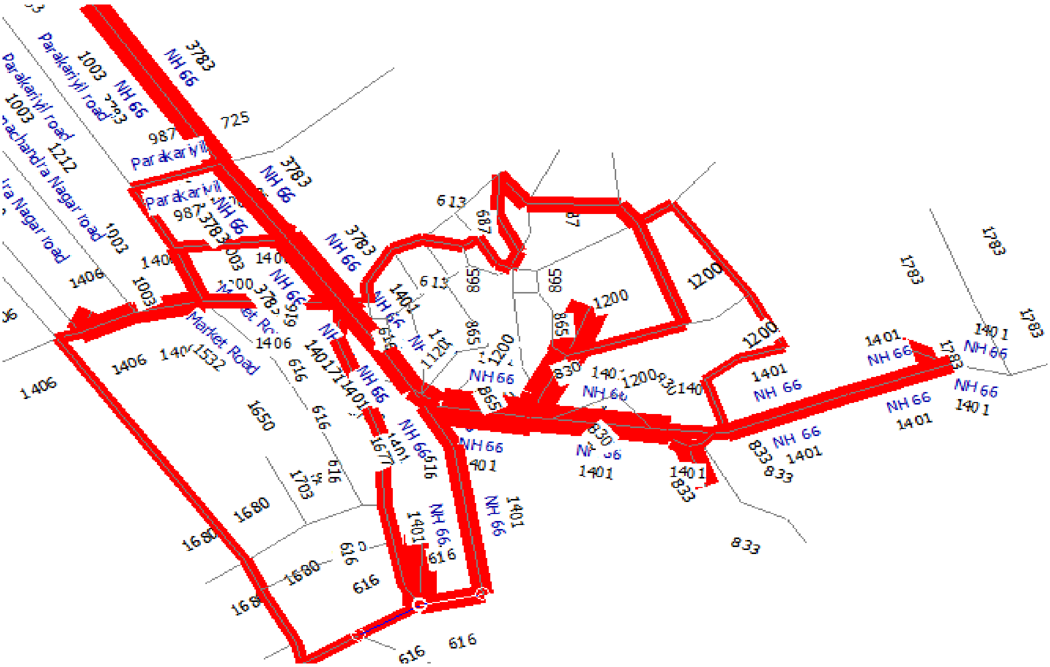

Fig. 9. Trip Assignment Output

It was found from the four step model that several road links near the Kazhakoottam intersection were congested. FCI Road and Kumizhikara road were found to be congested even though the traffic volume in these roads is comparatively low. This can be attributed to the fact that these roads have low capacity to carry its existing traffic volume, especially during the peak hours. The congested links were identified as NH66, Kazhakoottam to AJ hospital road, Kazhakoottam – Menamkulam road, Kazhakoottam- Kulathoor road, FCI Road and Kumizhikara Road

The travel demand model developed using the CUBE software was validated by comparing the simulated volume obtained from the model and the observed volume from the study area. The errors in simulated volume on all the roads are obtained below 20%. This shows that the developed model is good.

5. Impact of Travel Demand Management (TDM) Measures

In order to analyse the impact of TDM measures, a public transit line file was coded to the assigned network in CUBE. All the necessary details like route, stops, headway, delays, speed etc. were given in the public transit route file. Non – transit legs were also generated after assigning public transit. Three travel demand management measures were analysed.

a) Providing feeder modes to public transportation.
b) Carpooling.
c) Limiting the distance between zone centroids and bus stops to 400m.

5.1. Providing feeder modes to public transportation

In this scenario, share taxi was considered as a feeder mode to public transportation. The combination of feeder mode and public transport was taken as the fifth choice for mode in the analysis. The variation in three influential variables were analysed. In-vehicle Travel Time (IVTT), Out-Vehicle Travel time, and Generalised cost. The generalized cost function was given in equation (9).

$$\text{Generalized Cost} = (0.5 * \text{Time}) + (0.00151 * \text{Distance}) + \text{Base Fare} \quad (9)$$

It was observed that the mode split for public transport increased from 2·2% to 8·4%, implying that around 25.88% of passengers would shift to public transportation if feeder connectivity were provided.

5.2. Car pooling

The modal split output obtained from the four-step model showed that there is a higher mode share of cars in zone 8 compared to other zones, having its origin and destination within zone 8. Hence an analysis was made to assess the impact of introducing carpooling to this particular zone. A roadside vehicle occupancy survey was carried out to identify the average occupancy of cars within that zone. The average occupancy was found to be 2.13. As per IRC-SP-30, the auto occupancy factor for car is 4.8. The following assumptions were made in view of assessing this scenario

i. 50% of the people are willing to change from Single Occupancy Vehicle (SOV) to carpooling.
ii. The average occupancy of cars considered in carpooling is 4.8.

Considering the above factors, the change in mode share was analysed. The resultant mode split showed that there was an increase of 16.32% shift from private cars to public/shared transit.

5.3. Limiting the distance between zone centroids and bus stops to 400 m

For analyzing this scenario, the distance of intercity bus-stop from the zone centroid is taken into consideration. Among the 8 zone centroids, three of them are within 400m from the bus stop. The remaining 5 zone centroids are more than 400m. The distance of these bus-stops was limited to 400m and the corresponding change in modal share was analysed. It was observed that when the distance was reduced, there is an increase of 12.88% modal shift from private to public transportation.

6. Conclusion

The major output of this study is a methodological analysis to develop and execute transport modelling and application of travel demand management measures using the macro-simulation software CUBE. The method considers the construction of a set of parameters that can be applied in evaluating TDM measures and examines its efficiency in terms of passenger benefits. From a practical point of view, the aim of the method is to establish opportunities for better connectivity to public transport systems and encouraging passengers to shift from private modes to public transport. Beyond the reported results, this study also highlighted the essential need for data and variables, in order to predict travel patterns and to design efficient transportation systems.

The study area was divided into eight TAZs. It was found that the major factors affecting trip productions were number of commuters in the study area, vehicle ownership and age. The trip attractions were influenced by factors such as total employment opportunities in the region and type or category of employment. Trip generation model showed that the trips between commercial/employment zones and residential zones were high. The result from the model shows that seven road links near Kazhakoottam intersection were congested. Validation results showed that the difference between simulated volume and actual volume for most of the roads was obtained below 20%. This shows that the model is accurate. Three travel demand management measures were considered. it was observed in all the three TDM scenarios, that there is an increase in modal shift from private vehicles to public transportation. When share taxi was introduced as a feeder mode to public transportation, there was an increase of 25.88% in modal share of public- transit. In the case of carpooling, the increase in modal shift to shared transit was 16.32%. In the case of limiting the distance of bus-stops from zone centroids to 400m, an increase of 12.88% in the modal share of public/shared transit was observed. The demand management measures analyzed in the study thus proved that the developed model system is effective to analyze the impact of various short term TDM measures by policy makers before implementation.

Acknowledgements
The authors are grateful to Transportation Engineering Research Centre (TRC), College of Engineering Trivandrum, funded by Government of Kerala, for sponsoring the project.

References
[1] AFANDIZADEH, S., ZAHABI, S., & KALANTARI, N., 2010. Estimating the parameters of Logit Model using simulated annealing algorithm: case study of mode choice modeling of Isfahan. *IJCE*, 8 (1), 68-78.
[2] ALEX, A. P., MANJU, V. S, ISAAC, K. P., 2019. Modelling of travel behaviour of students using artificial intelligence. *Archives of Transport*, 51(3), 7-19. DOI: https://doi.org/10.5604/01.3001.0013.6159
[3] ALONSO, B., IBEAS, A., DELL'OLIO, L., & SAINZ, O., 2010. Optimizing bus stop spacing in urban areas. *Transportation Research Part E: Logistics and Transportation Review*, 46(3), 446-458.
[4] ARENTZE, T. A., & TIMMERMANS, H. J., 2004. A learning-based transportation-oriented simulation system. *Transportation Research Part,* 38(7), 613–633.
[5] BADOE, D. A., & CHEN, C. C., 2004. Unit of analysis in conventional trip generation modelling: an investigation. *Canadian Journal of Civil Engineering,* 31(2), 272–280.
[6] BEN-AKIVA, M., 2010. Planning and Action in a Model of Choice. In: HESS S. & DALY A. (Eds.), *Choice Modelling: The State-of-the-Art and the State-of-Practice* (pp. 19-34). Bingley: Emerald.
[7] BERKI, Z., & MONIGL, J., 2017. Trip generation and distribution modelling in Budapest. *Transportation Research Procedia*, *Elsevier*, 27, 172-179.
[8] BROADDUS, A., LITMAN, T., & MENON, G., 2009. Transportation Demand Management. *German Federal Enterprise for International Cooperation (GIZ), Sustainable Urban Transport Project (think tank)* (pp. 118). Eschborn, Germany.
[9] CHINTAKAYALA, P., & MAITRA, B., 2010. Modeling Generalized Cost of Travel and Its Application for Improvement of Taxies in Kolkata. *Journal of Urban Planning and Development*, 136(1), 42.
[10] CHOUDHURY, C. F., BEN-AKIVA, M., & ABOU-ZEID, M., 2010. Dynamic latent plan models. *Journal of Choice Modelling*, 3(2), 50–70.
[11] CIRILLO, C., & AXHAUSEN, K. W., 2010. Dynamic model of activity-type choice and scheduling. *Transportation, Springer,* 37(1), 15–38.
[12] DEWAN, K. K., & AHMAD, I., 2007. Carpooling: A Step to Reduce Congestion (A Case Study of Delhi). *Engineering Letters*, 14(1), 61-66.
[13] GARLING, T., & SCHUITEMA, G., 2007. Travel Demand Management Targeting Reduced Private Car Use: Effectiveness, Public Acceptability and Political Feasibility. *Journal of Social Issues,* 63(1), 139 – 153.
[14] GHASRI, M., HOSSEIN RASHIDI, T., & WALLER, S. T., 2017. Developing a disaggregate travel demand system of models using data mining techniques. *Transportation Research Part A: Policy and Practice*, 105, 138–153.
[15] GOULIAS, K. G., 1999. Longitudinal analysis of activity and travel pattern dynamics using generalized mixed markov latent class models. *Transportation Research Part B*, 33(8), 535–558.
[16] HERAWATI, 2011. Trip Assignment Model with Consideration of Vehicle Emission: Case For Cimahi City. *Civil Engineering Forum*, XX/1, 1189-1200.
[17] HESS, S., & TRAIN, K. E., 2011. Recovery of

inter-and intra-personal heterogeneity using mixed logit models. *Transportation Research Part B*, 45(7), 973–990.

[18] KADIYALI, L. R., VENKATESHA, M. C., et al., (2009) Manual on Economic Evaluation of Highway Projects in India. *IRC special publicationNo.30, The Indian Roads Congress,* New Delhi

[19] KALICA, M., & TEODOROVIC, D., 2003. Trip distribution modelling using fuzzy logic and a genetic algorithm. *Transportation Planning and Technology*, 26(3), 213-238.

[20] KARIMI, F., SULTANA, S., SHIRZADIBABAKAN, A., & SUTHAHARAN, S., 2019. An enhanced support vector machine model for urban expansion prediction. *Computers, Environment and Urban Systems*, 75, 61–75.

[21] KITAMURA, R., 1990. Panel analysis in transportation planning: an overview. *Transportation Research Part A*, 24(6), 401–415.

[22] KOPPELMAN, F. S., 1983. Predicting transit ridership in response to transit service changes. *Journal of Transportation Engineering*, 109(4), 548–564.

[23] KUMAR, A., & PEETA, S., 2014. Slope-Based Path Shift Propensity Algorithm for the Static Traffic Assignment Problem. *International Journal for Traffic and Transport Engineering*, 4(3), 297 – 319.

[24] LANE, R., POWELL, T. J., & P. PRESTWOOD-SMITH, 1973. *Analytical Transport Planning*. (2nd Ed.). New York: John Wiley and Sons, (Chapter 2).

[25] MAHMOOD, M., ABUL, B. MOHAMMAD, & AKHTER, S., 2009. Traffic Management System and Travel Demand Management (TDM) Strategies: Suggestions for Urban Cities in Bangladesh. *Asian Journal of Management and Humanity Sciences*, 4(2-3), 161-178.

[26] MCFADDEN, D., & TRAIN, K., 2000. Mixed MNL models for discrete response. *Journal of Applied Economics*, 15(5), 447–470.

[27] MCNALLY, M. G., 2000. The four-step model. In: D. A. HENSHER & K. J. BUTTON (Eds.), *Handbook of transport modelling* (pp. 35–42). Netherlands: Elsevier Science.

[28] MEYER, M. D., & MILLER, E. J., 2000. *Urban transportation planning: a decision-oriented approach*. (1st Ed.). New York: McGraw-Hill Publishers Inc, (Chapter 7).

[29] MOUNIR, A., 2014. Calibrating a trip distribution gravity model stratified by the trip purposes for the city of Alexandria. *Alexandria Engineering Journal*, 53(3), 677-689.

[30] NOEKEL, K., & WEKECK, S., 2009. Boarding and Alighting in Frequency-Based Transit Assignment. *Transportation Research Record*, 2111, 60-67.

[31] ORTUZAR, J. D., & WILLUMSEN, L. G., 2001. *Modelling transport*. (4th Ed.). West Sussex, UK: John Wiley & Sons Book Publishers, (Chapter 4).

[32] PAPACOSTAS, C. S., & P. D., PREVEDOUROS, 2001. *Transportation Engineering and Planning.* (3rd Ed.). New Jersey: Pearson Education Inc., (Chapter 8)

[33] PAUL, A., 2011. Axial Analysis: A Syntactic Approach to Movement Network Modeling. *Institute of Town Planners, India Journal*, 8(1), 29 – 40.

[34] PENDYALA, R., KITAMURA, R., & PRASUNA REDDY, D., 1998. Application of an activity-based travel-demand model incorporating a rule-based algorithm. *Environment and Planning B*, 25, 753–772.

[35] PENDYALA, R., & PAS, E., 2000. Multi-day and multi-period data for travel demand analysis and modeling. *Transportation Research Circular E-C008: Transport Surveys: Raising the Standard*, *TRB, National Research Council*, IIB-1–IIB-22.

[36] PENDYALA, R. M., KITAMURA, R., KIKUCHI, A., YAMAMOTO, T., & FUJII, S., 2005. Florida activity mobility simulator: overview and preliminary validation results. *Transportation Research Record*, 1921(1), 123–130.

[37] PENDYALA, R. M., 2009. Challenges and opportunities in advancing activity-based approaches for travel demand analysis. In: KITAMURA, & RYUICHI (Eds.), *The Expanding Sphere of Travel Behavior Research: Selected Papers from the 11th International Conference on Travel Behavior Research* (pp. 303). Bingley: Emerald.

[38] POUREBRAHIM, N., SULTANA, S., NIAKANLAHIJI, A., & THILL, J. C., 2019. Trip distribution modeling with Twitter data. *Computers, Environment and Urban Systems*, 77, 101354.

[39] ROY, J. R., & Thill, J. C., (2003) Spatial interaction modelling. *Papers in Regional Science*, 83(1), 339–361.

[40] SAHIL, S. M., MEET, D. P., VIVEK, S. S., MONTU, B. D., & YOGESH, K., 2017. Trip Distribution of Commercial Vehicle: A Case Study for Rajkot City. *Journal of Transportation System*, 2, 1- 12.

[41] SHEPPARD, E., 1995. Modeling and predicting aggregate flows. In: S. HANSON (Eds.), *Geography of urban transportation* (pp. 100–128). New York: The Guilford Press.

[42] SIKKA, R. P., DUTTA, P. K., et al., (1994) Guidelines for the Design of At-Grade Intersections in Rural and Urban Areas. *IRC special publication No.41, The Indian Roads Congress,* New Delhi

[43] SIMINI, F., GONZALEZ, M. C., MARITAN, A., & BARABASI, A. L., 2012. A universal model for mobility and migration patterns. *Nature*, 484(7392), 96–100.

[44] SUPERNAK, J., TALVITTIE, A., & DE JOHN, A., 1983. Person-category trip-generation model. *Transportation Research Record*, 944, 74-83.

[45] SURESH, M., & HARISH, S., 2016. A study of carpooling behaviour using a stated preference web survey in selected cities of India. *Transportation Planning and Technology*, 39(5), 538-550.

[46] VEDAGIRI, P., & ARASAN, V. T., 2009. Estimating Modal Shift of Car Travelers to Bus on Introduction of Bus Priority System. *Journal of Transportation Systems Engineering and Information Technology*, 9(6), 120-129.

[47] WAINAINA, S., 2003. Probabilistic models of transport modes selection in activity chains. *Scientific Journal of Silesian University of Technology. Series Transport.* 2003, 47, 503-512.

[48] WILLIAM, A. MARTIN, NANCY, A., & MCGUCKIN, 1998. NCHRP Report 365: Travel Estimation Techniques for Urban Planning. *TRB, National Research Council*, National Academy Press, Washington D. C.

[49] WILSON, A. G., 1998. Land-use / transport interaction models past and future. *Journal of Transport Economics and Policy*, 32(1), 3-26.

[50] XIONG, C., & ZHANG, L., 2013. Positive model of departure time choice under road pricing and uncertainty. *Transportation Research. Record*, 2345(1), 117–125

[51] XIONG, C., CHEN, X., HE, X., GUO, W., & ZHANG, L., 2015. The analysis of dynamic travel mode choice: a heterogeneous hidden Markov approach. *Transportation*, 42(6), 985–1002.