Defining transit accessibility with environmental inputs

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Abstract

This paper defines transit access incorporating the system attributes, viz, availability of access modes, their availability distance from residence, the difference in detour and airline distance to transit station and the condition of fixed facilities and flow entities, the shift potential under the effect of policies and the economic implications of pollution loading. The analysis is based on revealed and stated preference data. A maximum information procedure is developed to identify the shift potential due to the provision of better access conditions. A model is developed using joint estimation approach for the prediction of mode shares under policy effects. The environmental transit accessibility index, defined in this study, considers the effect of socioeconomic characteristics of the commuter, the economic and environmental implications and the behaviour of commuter under the hypothetical scenarios. The index is defined both for base year and for scenario year. A scale for evaluating environment transit accessibility is proposed. The approach is found defining transit accessibility satisfactorily for the study area.

Keywords: Accessibility; Transit services; India; Urban transport

1. Introduction

Accessibility is the key to spatial interaction. With a shift in land use planning towards the idea of developing suburban centers, the term has gained significance. But the mass transit systems, providing access to such centers, run on predefined and pre-established routes and cannot penetrate the inner areas or reach the outer peripheries. In such conditions feeder services to transit facilities
become very important. These may be walk, bicycle, tricycle, bus, or intermediate public transport like auto-rickshaw or taxi. Recently the share of motorized modes for transit access has increased, resulting in environmental pollution and traffic circulation problem near transit facilities. Therefore, the need is to coordinate, efficiently and effectively, the access modes to transit facility.

In this respect, a study was taken up in Mumbai (Bombay) city, India. The backbone of commuting in the city is suburban rail system, which operates on three corridors. The BEST (Brihan Mumbai Electric Supply and Transport Undertaking) public buses provide support to it in carrying 86% of the peak period load. The other modes mentioned above, with the exception of manual tricycle, are in use as access and egress modes to rail and bus facilities. The objectives of this study are, to examine the existing pattern of access trips to rail transit through the collection of revealed and stated information from randomly selected households, to develop a policy sensitive access mode choice model, and to define accessibility to transit with inputs from socio-environment aspects.

The approach is based on the revealed preference (RP) and stated preference (SP) information. The analysis requires evaluation of access environment attributes, and the identification of shift potential and modal shares under the effect of various policies. Based on these inputs an environmental transit accessibility index and scale is devised—the environment transit accessibility index (ETAI).

2. Conceptual and theoretical framework

2.1. Environmental transit accessibility index

The choice of access mode for accessing transit station is supposed to be controlled by the socioeconomic characteristics of the household/individual and the characteristics of the system. The access environment, so far, has been defined using some of the attributes relating to access facilities like sidewalk and bus stop, and proximity of destination (Evans IV et al., 1997). The approach presented here incorporates socioeconomic and environmental aspects along with the above mentioned aspects in defining ETAI. This is outlined in the following paragraphs.

2.1.1. Conceptual model

The conceptual model of ETAI can be defined in its functional form as follows

\[ \text{ETAI} = \Psi(M_{af}, D_t, C_i, S_p, E_s) \]  

(1)

where \( M_{af} \) (mode availability factor) = \( \phi(N_{ma}, A_d) \); \( D_t \) (detour factor) = \( \varphi(D_d, D_s) \); \( C_i \) (access environment condition index) = \( \Omega(R_a, B_s, S_w) \); \( S_p \) (shift potential) = \( \omega(A_s, S_e) \); and \( E_s \) (environmental saving) = \( \zeta(E_i, S_c) \).

ETAI can be defined with under policy effects as

\[ \text{ETAI}_{\text{Policy}} = (M_{af} + D_t + C_i + S_p) \exp(E_s/E_{ms}) \]  

(2)

where \( E_{ms} \) = maximum possible environmental savings.

In the base year when no policy is introduced the shift potential and the environmental saving will get eliminated and the equation reduces to
The simplified flow chart for computing ETAI is presented in Fig. 1.

\[ \text{ETAI}_{\text{Base}} = (M_{af} + D_f + C_i) \]  \hspace{1cm} (3)

The shift potential is based on maximum information procedure (MIP) and is a function of system attributes \((A_s)\) and socioeconomic characteristics of the commuter \((S_c)\). \(^1\) Willingness to

\(^1\) This is a modification of one suggested by Brog (1982).

2.1.2. Computation of attributes

The mode availability factor \((M_{af})\) is a function of access modes available and their distance from residence. The availability of access modes \((N_{ma})\) enters as a fraction of maximum number of access modes \((N_{tm})\) available to the commuter. The availability distance \((A_d)\) enters as a difference with respect to average availability distance \((A_v)\), taken as fraction over average availability distance. The assumption is that the increase in the availability of access modes should produce positive effect and the increase in availability distance of modes from residents should create negative effect.

\[ M_{af} = \left[ \frac{N_{ma}}{N_{tm}} + \frac{(A_v - A_d)}{A_v} \right] \times 100 \quad \text{where} \quad 200 > M_{af} > -100 \quad \text{(for} \ A_d \approx 2A_v) \]  \hspace{1cm} (4)

The detour factor \((D_f)\) is taken as a function of detour distance \((D_d)\) and the airline distance \((D_a)\) of the residence from the transit station. The assumption is that the detour distance cannot be less than the airline distance but if it is more than airline distance it should cause a negative effect.

\[ D_f = -\left[ \frac{(D_d - D_a)}{D_a} \right] \times 100 \quad \text{where} \quad 0 > D_f > -100 \quad \text{(for} \ D_d \approx 2D_a) \]  \hspace{1cm} (5)

The condition index \((C_i)\) is taken as the weighted sum of the condition of walkway \((S_w)\); bus stop or auto-rickshaw stand \((B_s)\); and condition of access road surface \((R_a)\).

\[ C_i = \frac{S_w + B_s + R_a}{3} \quad \text{where} \quad 100 > C_i > 0 \]  \hspace{1cm} (6)

Fig. 1. Procedure for computation of ETAI.
shift was posed to only commuters who were not accessing transit station by walk or bicycle. Commuters were provided with complete information in stages, regarding the walk or bicycle scenario. This provided information initially related to the better walk/bicycle facility, the environment soundness comparison of the modes, the constraints on the use of walk/bicycle, and the enhanced walk/bicycle facility scenario before finally recording the subjective willingness of the commuter to switch. (Fig. 2). The willingness% is factored to get the most conservative value of shift potential (Couture and Dooley, 1981).

In the case of environmental saving, environmental loading values are available for different categories of vehicles that can be correlated with vehicular flow to get% unit environmental loading ($E_l$) of different categories of vehicles. The maximum possible environmental saving ($E_{ms}$) can be computed as the sum of the multiplication of% unit environmental loading by non-green modes and respective% modal shares. The environmental saving ($E_s$) under the effect of policies can be computed as the sum of the multiplication of% unit environmental loading by a non-green mode with the respective% change in modal shares ($S_c$) due to policy presentation. These will enter the exponential part of the ETAI function.

### 2.2. Joint estimation of model

A common theoretical base for generating discrete choice models is the random utility theory (Domencich and McFadden, 1975). This postulates that an individual ‘$q$’ belonging to a homogeneous population ‘$Q$’, acts rationally, possessing complete information and based on this assigns a net utility $U_i$ to an alternative ‘$i$’ belonging to the set of available alternatives ‘$A$’. The alternative ‘$i$’ will be chosen, if and only if,

$$U_i > U_j, \quad j \neq i \quad \text{and} \quad j \in A$$

(7)

Utility has two components, one measurable and other a random error term. In the case of RP data this random error term ($e_i$) is associated with the independent variables. But, when dealing with SP data, the observations used are pseudo and results in pseudo-utility ($\bar{U}_i$). The forecasts will then get affected by the standard deviation of the error term ($\eta_i$) associated with the SP preferences (Bates, 1988). This may become ineffective if the deterministic components of the two
data sets can be made same. Bradley and Daly (1992) have suggested a scaling approach, which correlates the variance of error term of different observations via a scale factor:

\[ \mu^2 = \frac{\text{var}(e_i)}{\text{var}(\eta_i)} \]  

(8)

Based on the framework suggested by Ben-Akiva and Morikawa (1990) for the cases requiring a combination of data from different sources, utility functional forms can be written for an alternative \( i \in A \)

\[ U_{i}^{\text{RP}} = \alpha x_{i}^{\text{RP}} + \beta y_{i}^{\text{RP}} + \epsilon_i \]  

(9)

\[ \mu U_{i}^{\text{SP}} = \mu(\alpha x_{i}^{\text{SP}} + \gamma z_{i}^{\text{SP}} + \eta_i) \]  

(10)

where \( \alpha, \beta, \gamma \) are parameters to be estimated; \( x^{\text{RP}} \) and \( x^{\text{SP}} \) are vectors of common attributes to both type of data; and \( y^{\text{RP}} \) and \( z^{\text{SP}} \) are the vectors of attributes specific to RP or SP data, respectively. If the error terms of both data are assumed to be independent and distributed as Gumbel with zero mean, then the choice probabilities can be computed using a logit structure. But the maximum likelihood function in this case will be a non-linear problem as the scale factor gets multiplied with all the parameters to be estimated.

Ben-Akiva and Morikawa (1990) and Bradley and Daly (1997) suggested two basic approaches, the sequential estimation approach and simultaneous estimation approach, respectively, for dealing with the non-linearity in the functional form. The simultaneous estimation approach is used here. The key to its use lies in the estimation of the coefficient of common variable \( X \) that appears in both the utility functions. This is estimated using information from both sets of the data. The necessary assumption in joint estimation is that the marginal utility of each common variable is equal in each of the context. Another issue involves the interdependency between SP observations. This makes the assumption that the variance of unmeasured components \( \epsilon \) and \( \eta \) is equal impossible. But previous studies have found the practical problems caused by this assumption are limited (Bradley and Daly, 1997).

The construction of an artificial tree structure (Fig. 3) can solve the problem of non-linearity. ALOGIT (Hague Consulting Group) software can be used for estimation. The tree has as many elementary alternatives as there are in RP and SP sets combined. The RP alternatives emerge directly from the root, whereas, the SP alternatives are placed as trees. The RP alternatives are modelled using the nested structure and SP alternatives are modelled using the tree structure. With SP alternatives, each nest comprises of only one alternative. The mean utility of the dummy-alternative can be computed as (Daly, 1987)

![Fig. 3. Artificial nested-tree structure for mixed RP/SP estimation.](image-url)
\[ V^{\text{COMP}} = \mu \log \left( \sum \exp(V^{\text{SP}}) \right) \]  
\( (11) \)

As there is only one alternative in the nest, the expected maximum utility (EMU) of the nest equals the utility of the alternative itself;

\[ V^{\text{SP}} = aX^{\text{SP}} + \gamma Z^{\text{SP}} \]  
\( (12) \)

and the utility of the nest is

\[ V^{\text{COMP}} = \mu(aX^{\text{SP}} + \gamma Z^{\text{SP}}) \]  
\( (13) \)

which is exactly the same as required by Eq. (10). The scale factor should take the same value for all the SP alternatives. Further, as individuals are not modelled as choosing from among the RP and SP alternatives simultaneously, the assumption of the scale factor not exceeding unity, does not apply. If the scale factor is higher than unity, then it implies that SP data has less noise than the RP data (Ortuzer and Willumsen, 1996).

3. Study area and data structure

The Mumbai region (Fig. 4) is used for analysis. Face-to-face personal interview household surveys were conducted relating to two transit stations—Ghatkopar on the central rail corridor and Vile Parle on the western rail corridor. The revealed and stated information was collected from 1394 households, constituting 1.73% of the households (Rastogi and Rao, 2002). Nearly 50% commuters access a transit station by walking and 30% use bus (Table 1) Around 82% trips were found to be work related. The average household income was Rs. 12150 ($1 = Rs. 47) and the average household size was 4.63. Around 71% households had no vehicle at home. Of the remaining households, 8% had a car or other vehicles, 12% had motorised two-wheeler and bicycle and 9% had bicycle only.

The revealed and stated information was collected after standardizing the questionnaire (Rastogi and Rao, 2002). Mixed RP/SP data were used in the modelling to incorporate the salient features of both the approaches.

The RP information was collected from 1449 respondents. It included household and vehicular characteristics, trip makers’ characteristics, trip characteristics and information on access. The five access modes were considered walk, bicycle, bus, auto-rickshaw/taxi and private vehicle (car/motorised two-wheelers).

Some of options presented were not experienced by the commuters and came in via scenarios. Two SP exercises were conducted. One relates to walkin (SP-1) and considers the households living within 1250 m from transit station. The other relates to bicycling (SP-2) and considers households living outside 1250 m and up to the extent of residential area parallel to the transit line or around 4500 m, whichever was greater. \(^2\) The paired-choice set design (Bates, 1998; Widlert, 1998; Pearmain et al., 1991) is used. The exercise for finding willingness to shift to green modes was presented to commuters who are at present not accessing station by walk or bicycle.

\(^2\) The boundaries were fixed based on the experience gained during a pilot survey.
The walk related attributes were compared with the levels of the access mode in use. Three attributes were used—walk facility type, walk access time and pedestrian crossing type.

Table 1
Distribution according to access mode choices

<table>
<thead>
<tr>
<th>Access mode</th>
<th>Choices made</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Walk</td>
<td>715</td>
<td>49.34</td>
</tr>
<tr>
<td>Bicycle</td>
<td>091</td>
<td>06.28</td>
</tr>
<tr>
<td>Auto-rickshaw/taxi</td>
<td>146</td>
<td>10.07</td>
</tr>
<tr>
<td>Bus</td>
<td>439</td>
<td>30.29</td>
</tr>
<tr>
<td>Car/two-wheeler</td>
<td>058</td>
<td>04.00</td>
</tr>
<tr>
<td>Total</td>
<td>1449</td>
<td>100</td>
</tr>
</tbody>
</table>

*SP-1 exercise:* The walk related attributes were compared with the levels of the access mode in use. Three attributes were used—walk facility type, walk access time and pedestrian crossing type.
Walk access time was fixed according to speed and ranges from 4.3 to 6.0 kph. Four levels, were fixed for the other variables. Seven sets, each comprising of four combinations of the policy options, were presented to commuters who were requested to mark the preferred option and mode in each set.

**SP-2 exercise:** Bicycling was compared with bus, auto-rickshaw, including taxi, and private vehicle, including car and two-wheeler. The attributes defined for modes were bicycle storage, bicycle lane type, bicycle parking fee, private parking distance from transit station, parking fee, increase in auto fare, type of access to the station, increase in bus fare, headway, type of service and guarantee of seat. The attribute levels were fixed in combination with each other for a mode under consideration—e.g., an increased parking fee was clubbed with a shorter parking distance from station. Hence the total policy combinations were reduced to two each for bus, auto-rickshaw and private vehicle category and to six for bicycle category. The resulted 12 paired combinations were arranged in three sets, each containing relatively homogeneous options (Polak and Jones, 1997; Hensher, 1994; Widlert, 1998).

Some variables were derived from the basic variables. A dependency factor was calculated as the number of non-workers per worker in the household. The detour distance of a transit station from home was based on the location of residents and relative to the transit station used. A detour factor was calculated as the difference proportional between detour distance and airline distance. The codes given to different occupation levels were adjusted to represent the decreasing order of occupation level. The access time by auto-rickshaw, bicycle and walk were recalculated based on the type of facility presented in the alternative policy option. The total data set was expanded based on the psuedo observations obtained in SP survey.

### 4. Data analysis and computation of ETAI

The model is built up by entering variables in the utility function of alternate modes. They enter the utility function as generic variables (they appear in the utility function of all modes in generic sense); as mode-specific variables (they appear in the utility function of those modes to which they are specific); and as mode-specific constants (take care of unaccounted error). The mode-specific variables require a logical process for their entry into the utility function of a mode because it may change sign when used with other mode. This can be done either on the basis of prior notions or on the basis of trial and error. A combination of both is used. The formal test made on the entry of a variable is whether it has a logical sign and is significant based on its $t$-statistic. Different combinations of the five elementary access modes under consideration (walk, bicycle, car/two-wheeler, bus and auto-rickshaw/taxi) were used to identify the most acceptable nested structure. The structure in Fig. 5 was found to be the most acceptable. This supports the hypothesis that correlation exists between walk, bicycle and bus, and between auto-rickshaw and private vehicle.

Travel time and travel cost are considered as the generic variables. Travel time includes out-of-vehicle travel time—walk time to the access mode, walk time from the access mode to the station and walk time from parking to the station, and in-vehicle travel time. Travel cost includes the fare paid for the passenger access mode or the cost of fuel and parking for private mode. The mode-specific variables entered are listed in Table 2. Variables found with illogical sign were eliminated from the specification. Four mode-specific constants were used, auto-rickshaw and private mode
from the RP set, walk from the SP-1 set, and and bicycle from the SP-2. The structural variables used are the coefficient estimate of EMU (LOGSUM) and the scale factors for the two SP data sets ($\mu_1$ and $\mu_2$). The LOGSUM lies between 0 and 1 but there is no restriction on the value of scale factors ($\mu_1$ and $\mu_2$). A linear formulation was used for defining the utility function of different modes.

Table 2
Mixed estimation using RP and SP data

<table>
<thead>
<tr>
<th>Variables</th>
<th>RP + SP-1 + SP-2 model</th>
<th>Specification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Travel time</td>
<td>–0.1968 (–14.6)</td>
<td>Generic</td>
</tr>
<tr>
<td>Travel cost</td>
<td>–0.004903 (–14.2)</td>
<td>Generic</td>
</tr>
<tr>
<td>Type of dwelling unit</td>
<td>–0.3588 (–5.1)</td>
<td>Bicycle</td>
</tr>
<tr>
<td>Time of day</td>
<td>–0.0007164 (–4.3)</td>
<td>Bus</td>
</tr>
<tr>
<td>Mode availability distance</td>
<td>0.6851 (16.6)</td>
<td>Bus</td>
</tr>
<tr>
<td>Relation to household head</td>
<td>–4.261 (–5.5)</td>
<td>Private vehicle</td>
</tr>
<tr>
<td>Walk facility type</td>
<td>2.079 (8.6)</td>
<td>Walk</td>
</tr>
<tr>
<td>Bicycle storage</td>
<td>0.1026 (0.5)$^a$</td>
<td>Bicycle</td>
</tr>
<tr>
<td>Bicycle lane</td>
<td>0.7101 (3.8)</td>
<td>Bicycle</td>
</tr>
<tr>
<td>Bicycle parking fee</td>
<td>–0.002416 (–3.5)</td>
<td>Bicycle</td>
</tr>
<tr>
<td>Station access type</td>
<td>0.1824 (1.8)$^b$</td>
<td>Auto-rickshaw/taxi</td>
</tr>
<tr>
<td>Service of bus</td>
<td>1.167 (6.0)</td>
<td>Bus</td>
</tr>
<tr>
<td>Headway</td>
<td>–0.1432 (–4.8)</td>
<td>Bus</td>
</tr>
<tr>
<td>Private parking fee</td>
<td>–0.00001917 (–0.1)$^a$</td>
<td>Private vehicle</td>
</tr>
<tr>
<td>Walk constant</td>
<td>–4.592 (–15.3)</td>
<td></td>
</tr>
<tr>
<td>Bicycle constant</td>
<td>–7.924 (–15.6)</td>
<td></td>
</tr>
<tr>
<td>Auto constant</td>
<td>–0.03116 (–0.1)$^a$</td>
<td></td>
</tr>
<tr>
<td>Pvt constant</td>
<td>6.136 (7.3)</td>
<td></td>
</tr>
<tr>
<td>LOGSUM</td>
<td>0.2990 (13.1)</td>
<td>Coefficient of EMU</td>
</tr>
<tr>
<td>Scale factor</td>
<td>SP-1: 0.4298 (37.9)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>SP-2: 0.3703 (22.0)</td>
<td></td>
</tr>
<tr>
<td>$\rho^2$</td>
<td>0.2632</td>
<td></td>
</tr>
<tr>
<td>Sample size</td>
<td>6500</td>
<td></td>
</tr>
<tr>
<td>Subjective value of travel time (Rs/h)</td>
<td>24.08</td>
<td></td>
</tr>
</tbody>
</table>

$^a$ Not significant at 95% confidence level.  
$^b$ Significant at 90% confidence level.

Fig. 5. Model structures.
The RP/SP joint estimation model as required for computing modal shares under policy options is presented in Table 2. The commuters place equal significance to the two generic variables—travel time and cost. Most of the variables are significant, except for bicycle storage and private vehicle-parking fee, which are not significant at the 90% confidence level and station access, which is significant at 90%. The value of walk constant is quite high and negative, probably due to the biased SP data towards SP-2 (5128 observations) compared to SP-1 (164 observations). The private vehicle constant is highly positive indicating a strong preference. The bicycle variable has a high negative value indicating negative inclination. The scale factors of SP-1 and SP-2 are less than one and highly significant showing that SP data had more noise. The coefficient estimate of EMU of nesting was found to be significantly different from unity at a 95% confidence level supporting the idea that correlation exists between walk, bicycle and bus, and between passenger and private vehicle. The subjective value of time is found to be 41% of average hourly household income which accord with other studies (Rao, 1995; Maharashtra State Road Development Corporation Limited, 2001; Spanos et al., 1997). The general goodness-of-fit of the model, as seen by rho-squared statistics Hensher and Johnson (1981), was found to be good.

Looking at policy effects, those found to produce the highest change in shares were,

- **Walk**: Safe, unhindered and direct walks connectivity causing reduction in walk access time by 28%.
- **Bicycle**: Provision of separate bicycle lanes and bicycle storage adjacent to station causing reduction in bicycle access time by 25%.
- **Private vehicle**: Provision of private vehicle (motorised) parking at 500 m from the transit station and increasing parking fee by 50%.
- **Auto-rickshaw**: Restricted auto-rickshaw access to transit station, with substantial walk at the end of trip causing 40% increase in access time. Also increase in travel cost by 50%.
- **Bus**: No standing in bus i.e. guarantee of seat and increase in bus fare by 22%.

The changes in modal shares are presented in Table 3. These are used in combination with environmental loading for computing environmental savings. The environmental loadings per percent share of non-green modes are in Table 4.

The MIP approach was used for computing the maximum shift potential towards green modes—walk, bicycle and bus (Fig. 6). If the commuter declined to use a green modes as an access mode then it was recorded under ‘Yes’. The responses to the presentation of environmental statement were almost 50–50 but in the case of presentation of constraints and the modified connectivity to transit station the responses were divided on a one to two ratio in favour of no. The higher non-response for the modified facility was probably due to a poor understanding of the scenario. The shift potential ($S_p$) was found to be 9.3%. The environmental consciousness appears to be higher in the Vile Parle (East) area compared to Ghatkopar (East). This is probably due to different literacy rates. The shift potential was found to be more in Ghatkopar (East) compared to Vile Parle (East).

The computation of ETAl is based on the calculation of attribute values. The maximum number of modes ($N_{ms}$), that might be available to any commuter in the study area, was six. The average distance of availability of modes ($A_v$) from the residence, the predicted maximum possible shift ($E_{ms}$) from the green modes, the shift potential ($S_p$) and ETAl for whole area, Vile Parle
and Ghatkopar (East) are seen in Table 5. Based on Eqs. (2) and (3) the ETAI\textsubscript{BASE} may range between \(200\) and \(300\), and ETAI\textsubscript{POLICY} may range between \(543.65\) and \(883.44\). These values were transformed into an ETAI–scale, both for base year and under scenario condition (Table 6). After getting all the required information the ETAI values were computed under different policy conditions (Table 7).

In case of individual policies for causing shift towards green modes, the walk policy and auto-rickshaw policy are found, in order, to be more effective. The combination of different policies create maximum modal shift. Walk policy is found to be less effective than auto-rickshaw and private vehicle policy in Ghatkopar (East). The reason might be that in case of private vehicles there are no parking fees and no official parking lots near the transit station. Commuters park their vehicles on the street near the station. Therefore, the increase in parking distance and imposition of any parking fee works as a deterrent. Similarly, with auto-rickshaws, these drop a commuters at the door to the transit station. A restriction of immediate access, causing a substantial walk and any increase in fare are looked as reducing the utility of that mode. The walk policy was not found as effective as in Vile Parle (East). Already 95\% of the commuters residing within the expected walk distance from transit station were walking leaving very limited scope for further change. Ghatkopar (East) has a higher base year ETAI value than to Vile Parle (East). The base year ETAI represents the effect of the access environment of transit station in terms of the conditions of road, bus stop/auto stand and sidewalk, the number of access modes available,
the distance of their availability from residences and the effect of difference in airline and detour
distance. The Ghatkopar (East) area shows a higher positive effect of availability of modes, a less
negative effect of detour distance but higher negative effect of availability distance. The overall environmental transit accessibility seems satisfactory for all the conditions. The low value of ETAI is because all of the attributes are effective only up to 40% to 50% of their maximum value.

5. Conclusion

The considerable degree of reliance on motorized modes, even for short distance commuting and accessing suburban rail systems results in high levels of pollution near such facilities. The ETAI index incorporates a range of attributes and their effects—the effect of socioeconomic characteristics, the environmental pollution, the cost of abatement (in indirect form) and the system characteristics from access environment. It can be seen as a socioeconomic-environment index defining transit accessibility in its complete form. The approach has wide applicability and can be used for all types of transit facilities and development forms. It can be easily applied for examining the effect of policy in pre-implementation stage and in post implementation period. The approach can work as a tool for the transportation and land-use planners for comparing different policies and development forms.

References


